

# Analysis of Intracranial Hemorrhage in Ct Brain Images Using Machine Learning and Deep Learning Algorithm

Dr.J.Sofia Bobby<sup>1</sup>, Annapoorani C.L<sup>2</sup>

<sup>1</sup> Associate professor, <sup>2</sup>Assistant Professor , Department of BME, Jerusalem college of Engineering

[sofiabobbyj@jerusalemengg.ac.in](mailto:sofiabobbyj@jerusalemengg.ac.in)

**ABSTRACT:** Medical imaging is the process of developing the representations of all the constituents of the body visually and constituting the body physiology along with organ functions. The medical images are extracted by different techniques such as MRI (Magnetic Resonant Imaging), CT (Computer Tomography) and are processed for medical assistance and treatment. The Objective of the proposed system is to find the existence or absence of Hemorrhage in CT brain images using Supervised Machine Learning and Deep Learning Algorithm. Brain injuries may cause intracranial hemorrhages (ICH) during traumatic. This condition could leads to some disability or it may leads to death if it is not properly diagnosed. The dataset is available online at the physionet web publicly. Grayscale Conversion, Image resizing and Edge Detection Pre-processing is carried out before finding hemorrhage. The images undergo pre-processing techniques and made it suitable for further processing. This article represents intracranial hemorrhage segmentation processing and a mixture of techniques like thresholding, histogram equalization, watershed, neural network, and region based growing in CT brain images. The better hemorrhage result is based on four segmentation techniques. The advantage of using Support Vector Machine (SVM) is that, it provides results with a clear margin of separation and it is very much effective in high dimensional spaces. Convolution Neural Network is very useful to allow scenes objects and faces and for finding patterns in images. CNN remove the need for feature extraction manually by getting right from image data and using patterns or samples to classify images. Finally the result of segmentation is fed into classifier to find the Hemorrhage.

**Keywords:** Intracranial hemorrhage, segmentation, SVM and CNN classification

## I. INTRODUCTION:

### 1.1 Intracranial hemorrhage:

An intracranial hemorrhage is a blood bleeding that occurs inside the skull (cranium). Within the brain bleeding or around the brain is intracerebral hemorrhage. The Bleeding begins from artery into the brain is named a hemorrhagic stroke. An intracranial hemorrhage may be a sort of bleeding that happens inside the skull. Symptoms like difficulty with swallowing or vision, sudden tingling, difficulty in reading, or writing, weakness, severe headache, numbness, paralysis, loss of coordination, difficulty understanding and speaking and consciousness level or changes in alertness, indicates as lethargy, sleepiness, or coma. Bleeding inside the skull or brain is a medical emergency. So, It's necessary to urge the person to a hospital immediately to sort out the problem for the bleeding and begin medical treatment.

### 1.2 Imaging techniques of intracranial hemorrhages:

Computerized Tomography (CT) is best imaging techniques among all the techniques for hemorrhages assessment. CT is noninvasive technique, very fast and painless, and also it provides very higher contrast level between blood and tissue is present in almost all the hospitals. Hemorrhage emerge slightly brighter than other organ tissues in CT scans and has identification or recognition sensitivity of 90% for first 24 hours, 80% for the first three days, and about 50% for up to one week. The hemorrhage region of the tissues has to be

splitted in CT scans to estimate the ICH and IVH volume quantitatively. Picture segmentation technique design is a stimulating task to non-availability of anatomical models that record all the possible variations like shape, size, and texture with various composition, low SNR, innate artifacts and better image quality for medical applications.

Amutha et al proposed identifying MRI images which is stroke and for non stroke images. Image classification may be a hypercritical step for processing of automatic classification of brain stroke. Proper segmentation and classification of affected stroke regions are essential for accurate detection and diagnosis. Significant features are extracted using Gabor filter and Watershed segmentation. Then, the extracted features are classified using MLP (Multilayer Perceptron). A test has been carried on to calculate the efficiency of the proposed method with different number of features.

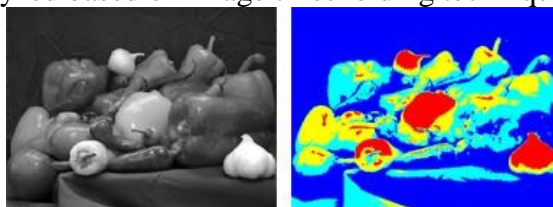
Computed tomography (CT) segmentation of the brain research is relatively fall in short of standard as said by Alxendra Lauric et.al. Since, MRI is best imaging technique at differentiating soft tissue, it's generally preferred over CT for brain imaging. In some cases, MRI is contraindicated and different scanning methods to be used. The soft tissue segmentation methods of CT brain data imaging is used in enhancing the utility of computed tomography for brain imaging is explored. Shuchi sainsi et.al proposed approach of multilevel segmentation gives mean value of 97.1% and computation time of 0.17 second on average. This approach gives good results.

## II. MATERIALS AND METHODS:

This article presents hemorrhage by intracranial segmentation technique in CT images using various techniques and thresholding and water shed methods are applied. MATLAB software is used as numerical analysis environment and it is applied here. Sobel filter which is applied for edge detection. Sobel filter is done for calculating the image intensity gradient at each pixel within the image. The results of applying it to a pixel on a foothold may be a vector that points across the sting from darker to brighter values.

## III. Segmentation:

Threshold segmentation is used to segment hemorrhages. Image segmentation method is a frequently used technique in digital image processing and used to separate an image into multifold parts or regions, and repeatedly on the features of the pixels in the brain image. Threshold segmentation forms a grayscale image and thresholding can be used to produce binary images. Images can be analyzed based on image thresholding techniques.

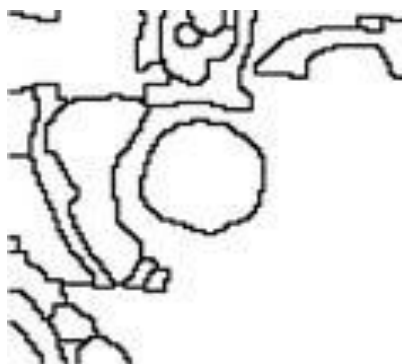


**Fig 3.1 Example for threshold Image**

### 3.1 Watershed segmentation:

Watershed remodel will unearth watershed ridge and catchment basins traces in a image picture by handling it as a mat floor wherein darkish pixels are low and mild pixels are high. Segmentation the use of the watershed transforms foreground items and heritage locations. In graphical representation, watershed traces can also be described at the nodes, sides, or hybrid traces on each nodes and edges. Watersheds can additionally be described inside the non-stop domain.

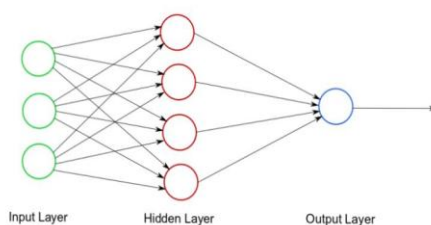
There additionally are many various algorithms to calculate watersheds. Watershed algorithm is employed in picture processing frequently for segmentation purposes.



**Fig 3.2. Watershed of the gradient**

### 3.2 Neural Network Segmentation:

A neural network is a synthetic neural network, consists of artificial nodes. So, a neural network is based on biological network and it is developed for true



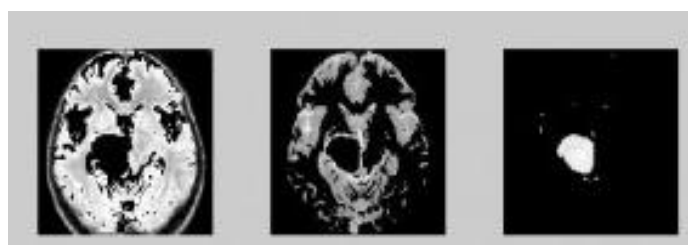
**Fig No: 3.3. Neural network segmentation**

biological neurons, for resolution artificial issues. The connections link of the biological nerve cell measured as weights. A positive weight shows degree excitant association, whereas negative weight shows repressive connections. All inputs square measure changed by a weight of the nodes and then summed. The mentioned activity is a linear activity of combination. An activation function rules the magnitude value of the output finally. The output is usually between 0 and 1 is an acceptable range, or it could be  $-1$  and  $1$  is an example for NN segmentation.

### 3.3 Clustering Segmentation:

K-means cluster is one amongst the popular algorithms in cluster and segmentation. K-means segmentation looks every image element (with RGB values) as a feature purpose having a

location in area. The fundamental K-means algorithmic program then haphazardly locates that variety of cluster centers in multidimensional activity area.



**Fig 3.4. Clustering segmentation**

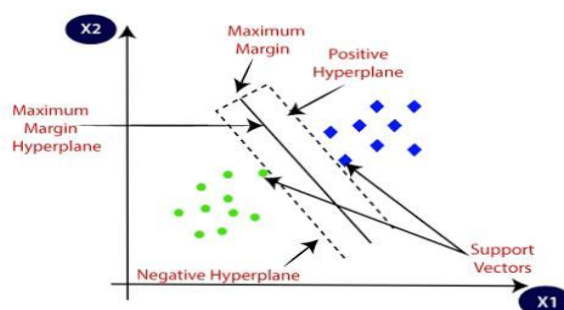
### 3.4 Otsu Segmentation:

Otsu's technique may be a one-dimensional distinct analog of Fisher's Discriminant Analysis, is expounded to Jenks optimisation technique, and is reminiscent of a globally optimum performed on the intensity bar chart. The final extension to multi-level thresholding was set out and computationally economical implementations have since been planned

## IV. Classifiers:

### 4.1. Support vector machine Classifier (SVM):

Support vector machines (SVM) are direct classifiers and it is based on the principle of margin maximization. They execute structural risk minimization, it develops the difficulty of the classifier with the focus of attaining great generalization performance.



**Fig No: 3.5.Support vector machine Classifier**

- Training data: the previous matrix set corresponds to antecedent seen pictures of an apple and pear.
- The obtained information consists of a picture born-again to an image matrix. The aim is to speculate mechanically what's there in the image like an apple or a pear.
- The support vector uses a kernel perform that may be a mathematics perform that equal the new information to the most effective brain like image from the information so as to forecast the unknown label picture like pear or an apple.
- Compared to other classifiers, SVM occur sturdy, correct predictions, area unit least tormented by buzzing information, and area unit less susceptible to over fitting. confine

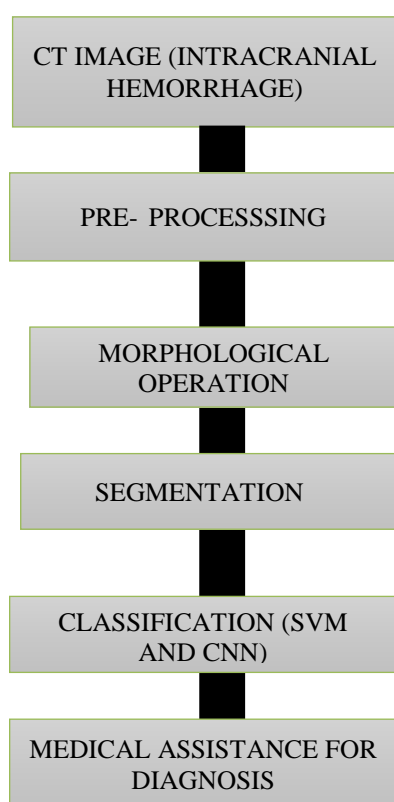
mind, however, that support vector machines are unit best suited for binary classification — after you have solely 2 classes (such as apple or pear)

## 4.2. Convolution neural network (CNN) Classifier:

CNN classifier constitutes a vast development in deep learning algorithms. It is used to detect if image of the brain contain a tumor or not and also used to find important features of data. Basically, it is a machine based learning algorithm to understand the features of the brain images in this proposed system.

## V. METHODOLOGY:

### 5.1. Workflow:



**Fig 5.1: Flow chart representing the procedure**

### 5.2. Pre-processing:

Technique of Pre-processing is applied to get better and enhanced image quality by removing the unwanted portions of the scanned data of the image.

#### a. Grayscale conversion

The CT images are converted to grayscale image to make it contrast in a way and to give the exact needed information. This transformation is formed to eliminate the colors and to spotlight any hemorrhages or abnormalities.

### **b. Resizing**

In image processing, resizing can be done to satisfy the properties of storage, display and other constraints. The display devices resolution might have maximum size and the scanned images might be of different size. So, the image is resized with specifications to bring out the constant. The 256x256 pixel is the resize value of the grayscale images.

### **c. Edge detection**

The detection of edges is carried out the boundary or to verify the presence of hemorrhage. Edge detector with sobel filter is used for this purpose. A multistage edge detection algorithm is used. Sobel filter is used to smooth the brain image in order to take out the noise and then gradients of the image intensity are obtained. Maximum suppression method followed by application of two threshold method to determine potential edges. Then detection of edges is completed by quash all the other edges that are delicate and strong edges are not connected.

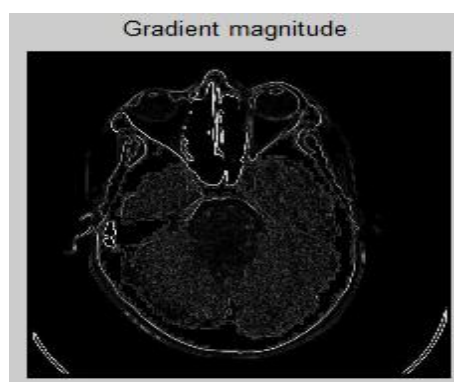
### **d. Edge sharpening**

The edges are made to contrast on the grey scale in order that image shall be easy for both morphological operations and image segmentation. Edges are defined as object surface boundaries. Sharpening refers to highlighting the edges such that if hemorrhage is detected its edges are cleaned.

### **5.3. Morphological operation:**

Morphological techniques are focused to remove imperfections. The binarized images are further processed by this system.

- a. Sobel operator use the gradients to learn the elevation map
- b. Markers of background are found using the utmost parts of the histogram of gray scale values.
- c. Binary thresholding is carried out to take out the undesired important regions from the Sobel image and this can be worked with Sobel image and superimposing marker.



**Fig 5.2: Gradient Magnitude of Intracranial Hemorrhage**

## 5.4 Thresholding technique:

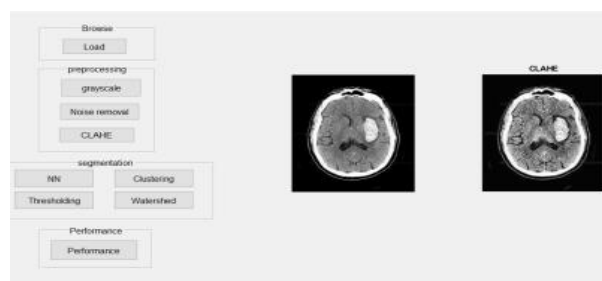
Thresholding techniques play an important role in imaging segmentation. It involves local techniques and global techniques. Therefore, Thresholding becomes a victorious tool to split objects from the surrounding. Thresholding method produces binary type image outputs whose one state would indicate the front objects while the zero state would indicate the background. Forefronts are indicated by gray-level 0 i.e. black and therefore the background is indicated as 255 best luminance in 8-bit images, or oppositely the forefront represents white and the background represents black.



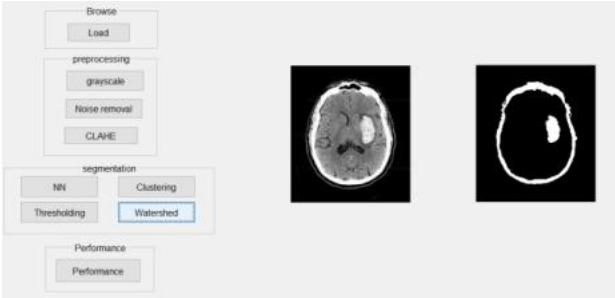
**Fig 5.3: Threshold Image of Intracranial Hemorrhage**

## VI. RESULTS AND DISCUSSION:

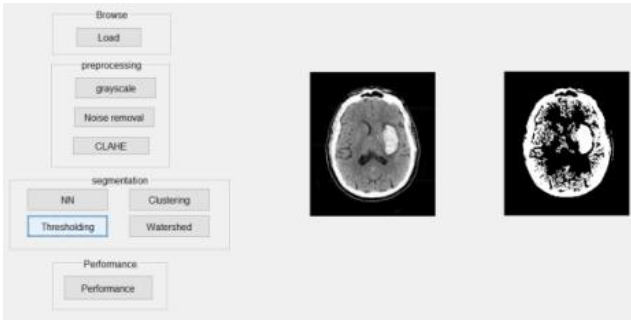
The proposed method could be trained successfully with CT images of the brain and the segmentation part is done to detect the Region of Interest. Segmentation is being employed to urge a smoothened image. The boundaries of regions are found to be continuous and there was a problem of over segmentation. The concept of marker based approach is employed to resolve this segmentation problem. Once there's a presence of hemorrhage, it is often classified for the kinds making it a multi-classification problem. The proposed system is well trained for various datasets of Brain CT images with and without hemorrhage.



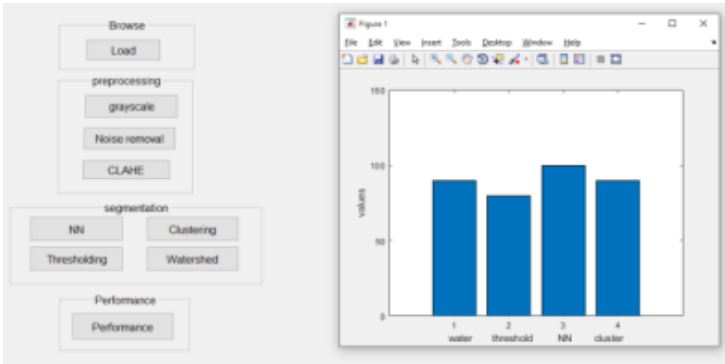
**Fig 6.1 Clustering**



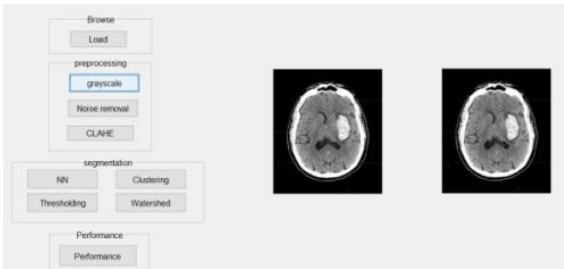
**Fig 6.2 Watershed**



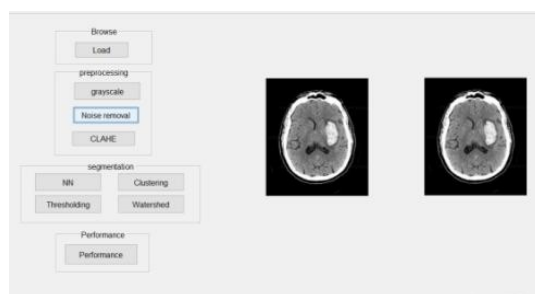
**Fig 6.3 Otsu segmentation**



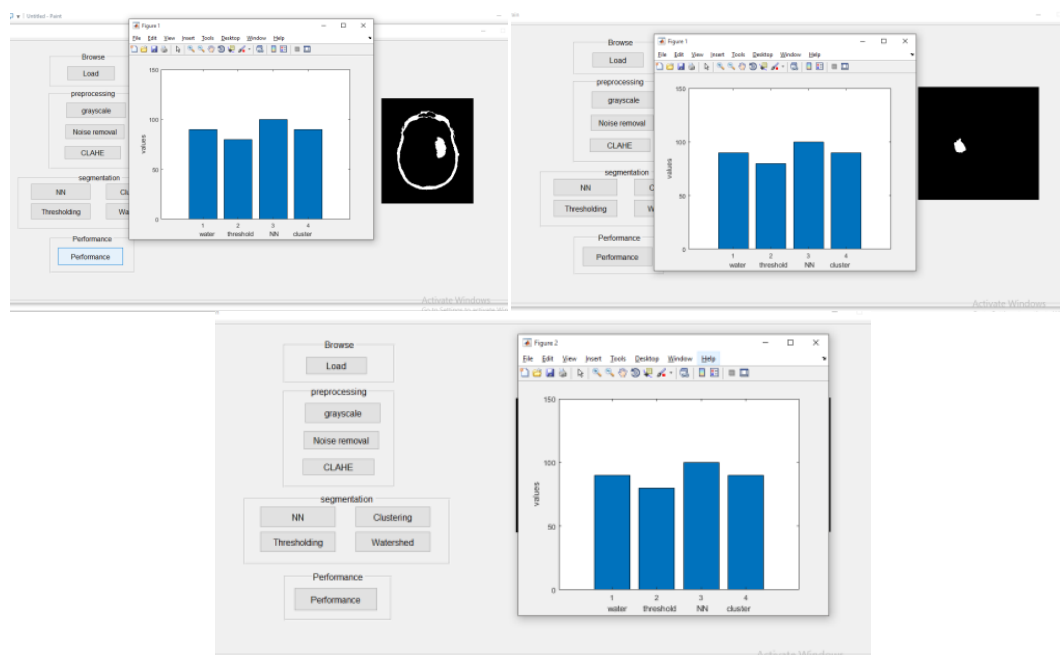
**Fig 6.4 Performance graph**



**Fig 6.5 Noise removal**



**Fig 6.6 Gray scale**



**Fig 6.7 Performance analysis for three images**

## VII. Conclusion and future works

The analysis of intracranial hemorrhage of CT brain images by different segmentation techniques like watershed, neural network, thresholding /OTSU method and clustering technique with the SVM and Convolutional Neural Network Classifiers results in segmentation of hemorrhage part within the brain. By comparing the the various segmentation, the Neural Network Segmentation gives accuracy values of 98.70 followed by the Watershed Segmentation value of 94.30 and followed by Clustering segmentation value of 90.3 and Thresholding segmentation value of 83.74.

The proposed results are invigorating and having better perfection for the three classification problem are often reached a best data set with very high resolution images taken right from the scanner of CT. Furthermore, feature extraction of various types and have specific techniques are often applied to enhance the performance of the system. Finally, ensemble different tools like Simulink toolbox and statistics and machine learning toolbox for classification are going to be contemplating as a progress work done to attain better accuracy in future. This procedure will permit the longer term to succeed in a

big level which will permit it to be a benefit to any medical formation to handle brain hemorrhages.

## References:

[1] H. P. Adams, G. del Zoppo, M. J. Alberts, D. L. Bhatt, L. Brass, A. Furlan, R. L. Grubb, R. T. Higashida, E. C. Jauch, C. Kidwell, P. D. Lyden, L. B. Morgenstern, A. I. Qureshi, R. H. Rosenwasser, P. A. Scott, and E. F. Wijdicks, Guidelines for the early management of adults with ischemic stroke. *Stroke*, 38(5):1655–1711, 2007.

[2] M. Al-Ayyoub, M. T. Irfan, and D. G. Stork. Machine learning of multi-feature visual texture classifiers for the authentication of Jackson Pollock's drip paintings. volume 7869, 2011.

[3] K. Al-Darabsah and M. Al-Ayyoub, Dr. J. Sofia Bobby. Breast cancer diagnosis using machine learning based on statistical and texture features extraction. In 4<sup>th</sup> International Conference on Information and Communication Systems (ICICS 2013), 2013.

[4] U. Balasooriya and M. Perera. Intelligent brain hemorrhage diagnosis using artificial neural networks. In IEEE Business Engineering and Industrial Applications Colloquium (BEIAC), pages 128–133, 2012.

[5] T. Chan. Computer aided detection of small acute intracranial hemorrhage on computer tomography of brain. *Computerized Medical Imaging and Graphics*, 31(4):285–298, 2007.

[6] M. Chawla, S. Sharma, J. Sivaswamy, and L. Kishore. A method for automatic detection and classification of stroke from brain ct images. In Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pages 3581–3584, sept. 2009.

[7] D. Cheng and K. Cheng. Multiresolution based fuzzy c-means clustering for brain hemorrhage analysis. In Proceedings of the 2nd International Conference on Bioelectromagnetism, pages 35–36. IEEE, 1998. WSEAS TRANSACTIONS on COMPUTERS Mahmoud Al-Ayyoub, Duaa Alawad, Khaldun Al-Darabsah, Inad Aljarrah E-ISSN: 2224-2872 404 Issue 10, Volume 12, October 2013

[8] A. Datta and B. Biswas. A fuzzy multi layer perceptron network based detection and classification of lobar intra-cerebral hemorrhage from computed tomography images of brain. In 2011 International Conference on Recent Trends in Information Systems (ReTIS), pages 257–262. IEEE, 2011.

[9] Z. Kerekes, Z. Tóth, S. Szénási, and S. Serpyán. Colon cancer diagnosis on digital tissue images. In 2013 IEEE 9th International Conference on Computational Cybernetics (ICCC), pages 159–163. IEEE, 2013.

[10] H. Liu, C. Xie, Z. Chen, and Y. Lei. Segmentation of ultrasound image based on morphological operation and fuzzy clustering. In Third IEEE International Workshop on Electronic Design, Test and Applications (DELTA), 2006.

[11] R. Liu, C. L. Tan, T. Y. Leong, C. K. Lee, B. C. Pang, C. Lim, Q. Tian, S. Tang, and Z. Zhang. Hemorrhage slices detection in brain ct images. In 19th International Conference on Pattern Recognition (ICPR 2008), pages 1 –4, dec. 2008.

[12] S. Loncaric, A. Dhawan, J. Broderick, and T. Brott. 3-d image analysis of intracerebral brain hemorrhage from digitized ct films. Computer Methods and Programs in Biomedicine, 46(3):207–216, 1995.

[13] S. Loncaric and Z. Majcenic. Multi resolution simulated annealing for brain image analysis. In Medical Imaging'99, pages 1139–1146. International Society for Optics and Photonics, 1999.

[14] MATLAB. version 7.13 (R2011b). The MathWorks Inc., Natick, Massachusetts, 2011.