Diagnosis & Classification of Brain Hemorrhage

Vincy Davis
Electronics & Telecommunication Department
DMCE, Mumbai University
Airoli, India
9167411165
vincy1992.vd@gmail.com

Dr.Satish Devane
Information & Technology Department
DMCE, Mumbai University
Airoli, India

***Abstract*—Brain Hemorrhage is a type of stroke, which occurs due to bursting of an artery in the brain, thus causing bleeding in the surrounding tissues. CT (Computed Tomography) images are used to diagnose bleeding and fractures in inner parts of the body. CT images are preferred over MRI (Magnetic Resonance Imaging) images due to wider availability, lower cost and sensitiveness to early stroke. These images are first preprocessed, performed morphological operations on and then segmented using watershed algorithm. This extracted image is given as an input to an artificial neural network for classification. It also gives information on the hemorrhage area and the hemorrhage percentage.**

Keywords— CT, MRI, Intracerebral Hemorrhage, Subdural Hemorrhage, Extradural Hemorrhage, Subarachnoid hemorrhage, ROC, GA, Watershed Algorithm, ANN, GLCM.

I. INTRODUCTION

Brain Hemorrhage is a type of stroke, which occurs due to the bleeding in or around the brain tissues as a result of ruptured artery. Due to an accident, trauma may affect the brain tissues thus causing swelling which may lead to edema pooled blood from surrounding tissues. This will accumulate to form a mass known as hematoma in brain. The symptoms of brain hemorrhage may vary depending on the amount of tissue affected, location of the bleeding & the severity of the bleeding. Medical experts usually advices Computed Tomography (CT) scan than a Magnetic Resonance Imaging (MRI) scan for checking internal bleeding or blood accumulation. A CT scanner transmits X-ray beams in an arc thus taking many pictures. This allows sensing of different levels of density and tissues inside a solid organ, and can provide detailed information about the body. Thus bleeding in the brain, especially from an injury, can be seen well on a CT scan than on a MRI scan. In this proposed system, CT images are used. These image after being pre-processed, are made to undergo certain morphological operations. Morphological image processing is a collection of non-linear operations related to the shape or morphology of features in an image. This technique probes an image with a small shape or template called as structuring element. The structuring element is positioned at all possible locations in the image and it is compared with the corresponding neighbor of pixels. Dilation and erosion are the two operators used in this system. In dilation, if the origin of the structuring element coincides with the 'black' pixel in the image, all pixels are made black, from the image covered by the structuring element. Similarly in erosion, the pixels are turned to ‘white’. After this, the image is segmented using Watershed Algorithm. Image segmentation is a process of partitioning the image into non-intersecting regions, so that each region is homogeneous. Exact location of required objects and boundaries in images can be found through image segmentation. In Watershed Algorithm, we consider the image as a topographic relief, where the height of each point is directly related to its gray level, thus the watershed lines separates the catchments basins that are formed. The watershed transform is computed on the gradient of the original image, so that the catchment basin boundaries are located at high gradient points. The classifier used in this process is an Artificial Neural Network (ANN). It is a computational model based on structure and function of animals nervous system in particular brain which is capable of machine learning and pattern recognition. ANNs are presented as system of interconnected neurons which exchange between each other. The neuron has two modes of operations: The training/learning mode and the using/testing mode. In a feed forward neural network, information flows in one direction along connecting pathways, from the input layer via the hidden layers to the final output layer.

II. TYPES OF HEMORRHAGE

As per bleeding in the brain, it can be divided into four types:

A. Intracerebral Hemorrhage (ICH)

This type of stroke occurs when the brain is deprived of oxygen due to an interruption of its blood supply. The location of ICH can be close to the surface or in deep areas of the brain. It is a type of stroke caused by bleeding within the brain tissues itself.

B. Subdural hemorrhage (SDH)

It is the collection of blood, accumulating in the potential space between the dura and arachnoid mater of the meninges around the brain. The meninges are the connective tissue membranes that line the skull and vertebral canal. It encloses the brain and the spinal cord.

978-1-5386-3852-1/17/$31.00 ©2017 IEEE

C. Extradural Hemorrhage (EDH)

It is the bleeding between the inside of the skull and the outer covering of the brain called as "dura". It is often caused by a skull fracture during childhood or adolescence. An extradural hemorrhage occurs when there is a rupture of a blood vessel, usually an artery, which then bleeds into the space between the "dura mater" and the skull.

D. Subarachnoid hemorrhage (SAH)

It is a life-threatening type of stroke caused by bleeding in the space surrounding the brain. A stroke is caused when the brain is deprived of oxygen because of an interruption of its blood supply. Subarachnoid hemorrhage is caused by ruptured aneurysm.

In the proposed system, the first two type of hemorrhages i.e., Intracerebral Hemorrhage (ICH) and Subdural Hemorrhage (SDH) are processed and classified.

III. LITERATURE SURVEY

R. Ganesan and S. Radhakrishnan (2009) has proposed segmentation of CT brain image using Genetic Algorithm (GA) to segment the image. It has been evaluated using receiving operating characteristics (ROC) curve analysis. Liu et al. has presented an automated detection of CT scan slices which contain hemorrhages. The detection method consists of two parts. The first part splits the scan slices into encephalic region and nasal cavity region. The second part focuses on encephalic region and detects abnormal slices. Both parts use Wavelet and Haralick texture model. Rajesh A. Rajwade uses image enhancement tools and medical filtering to diagnose brain hemorrhages along with geometrical and textural features, which is used as input to neural network and support vector machine. C. Amutha Devi and Dr. S. P. Rajagopalan proposed a method for classifying the brain MRI images into stroke and non-stroke images. In this method features are extracted from MRI images of brain using watershed segmentation and Gabor filter. Alyaa Hussein Ali et al. (2015) recently proposed the detection and segmentation of hemorrhage stroke from brain CT images using textural analysis. In study, the thresholding segmentation process is used to extract stroke region from CT image of brain. The median filter was used to remove noise from image and the statistical feature calculated using first order histogram. The first order histogram represents estimation of probability distribution function (PDF) for selected neighbourhood. The results as mean value represents white color in image. The higher mean gives indication that there is an abnormal part in brain. Mayank Chawla et al. (2009) presented an automated method to detect and classify an abnormality into acute and chronic infarct, and hemorrhage at the slice level of non-contrast CT images.

Issues in current identification methods:

The main problem present in the above methods is that the data becomes sensitive to noise. The systems using fuzzy clustering methods also need more iteration for achieving better detection result. In certain systems, feedback pulse-coupled neural network is used which increases the software complexity of the system. Thus in this proposed system, I have tried to overcome these issues.

IV. PROPOSED METHODOLOGY

In this system, the CT image of the brain undergoes certain preprocessing operations. In these operations, the image is converted into gray scale image, it is re-sized and the edges are detected. This preprocessed image is then made to undergo some morphological operations such that the texture of the image becomes smoother, the small holes are eliminated and gaps filled such that it helps in the next step of segmenting the image. Watershed algorithm helps to classify distinct regions in the system using watershed lines. This segmented image is given as an input to Grey Level Co-occurrence Matrix (GLCM) wherein different features are extracted. These features are given as input to the classifier i.e., ANN. Using the training phase, the superimposed images are compared to the original image, such that the type of hemorrhage is detected and the error calculated.

A. Flowchart

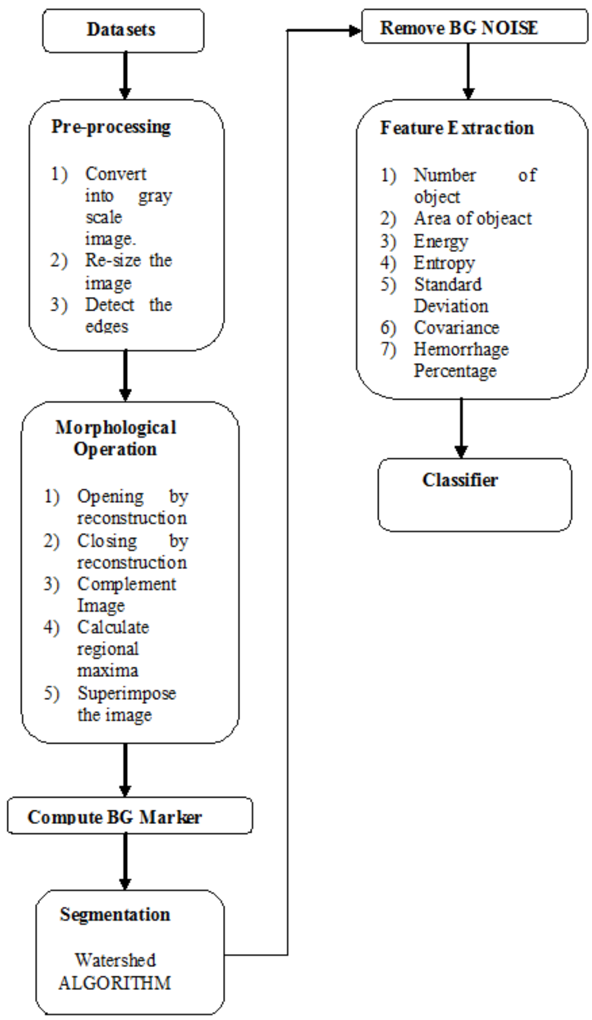


Fig. 1: Flowchart of the proposed system

B. *Datasets*

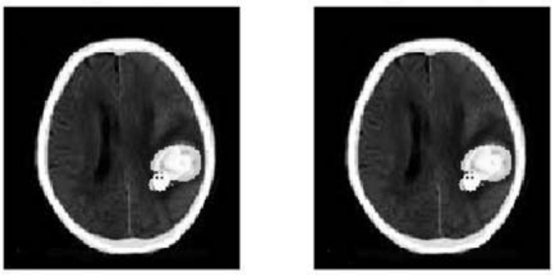
The dataset consists of 35 CT images of human brain. These images include 12 images of ICH, 9 images of SDH and 14 normal images. CT images helps in identifying image bone, soft tissues and blood vessels all at the same time. These images are converted in jpeg form to be uploaded to the system for pre-processing.

C. *Pre-processing*

Pre-processing improves the quality of an image. In this system, preprocessing techniques are developed to remove the skull portion surrounding the tissues.

1. Conversion of Image

The CT image is converted into gray scale image to make it contrast. The contrast image helps in giving exact information about the tissues.

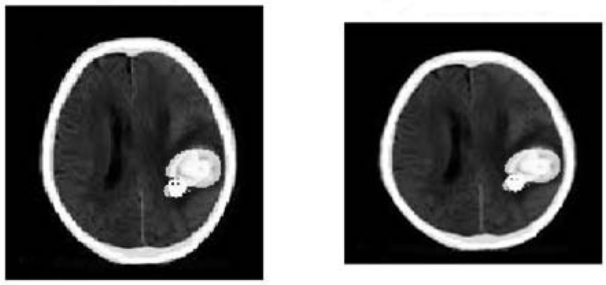


a) Original Image b) Gray Scale Image

Fig. 2 : a) Original Image b) Original Image converted into gray scale image

2. Re-sizing

Resizing is an important step in image preprocessing. It is required for various purposes such as display, storage and transmission of images. While displaying an image, the resolution of the display devises imposes constraints on the maximum size of the display screen. The acquired image is resized according to the requirement of the system. Resizing is changing the dimensions of an image. It is done so as it fits on the system user interface. The converted gray scale image is resized to 256 pixels by 256 pixels size.

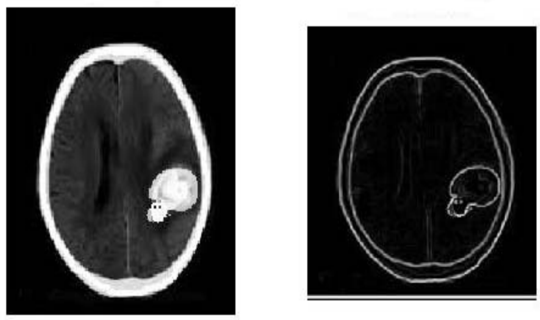


a) Original Image b) Resized Image

Fig. 3: a) Original Image b) Image resized as 256x256pixels

3. Edge Detection

Edge detection refers to the process of identifying and locating sharp discontinuities in an image. The discontinuities are abrupt changes in pixel intensity which characterizes boundaries of objects in a scene. Edges themselves are boundaries of object surfaces which often lead to oriented, localized changes of intensity in an image. In this system, Sobel operator is used for edge detection. The Sobel operator is based on convolving the image with a small, separable, and integer valued filter in horizontal and vertical direction and is therefore relatively inexpensive in terms of computations. Mathematically, the operator uses two 3×3 kernels which are convolved with the original image to calculate approximations of the derivatives - one for horizontal changes, and one for vertical.



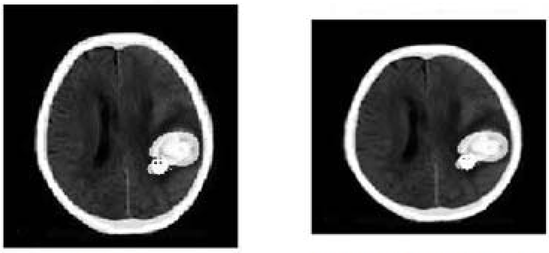
a) Original Image b) Edge detected Image

Fig. 4: a) Original Image b) Edges of the image is Detected

D *Morphological operation*

Dilation and erosion operators are further used in complex sequences of opening and closing.

- Opening consists of an erosion followed by a dilation and can be used to eliminate all pixels in regions that are too small to contain the structuring element.



a) Original Image b) Opening by reconstruction

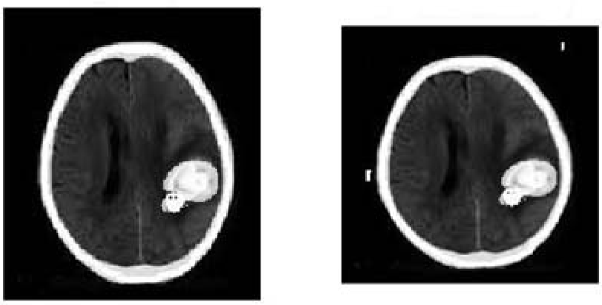
Fig. 5: a) Original Image b) Opening by reconstruction – Morphological Operation

- The Closing operation fuses narrow breaks, also eliminates small holes and fills gaps in the contours.

a) Original Image b) Closing by reconstruction

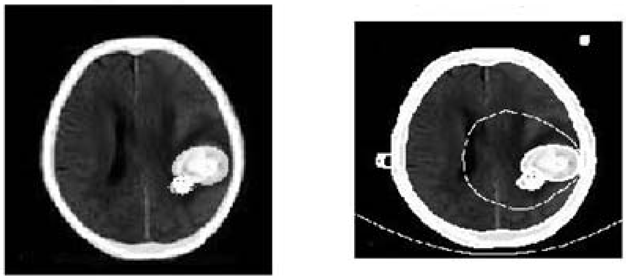
Fig. 6: a) Original Image b) Closing by Reconstruction-Morphological Operation

After opening and closing reconstruction operation, the complement of the gray scale image is taken, to calculate the regional maxima. Calculating the regional maxima of these reconstructed images is done to get smooth edge foreground objects. Later, we superimposed these markers on the original images.



a) Original Image b) Regional Maxima Image

Fig. 7: a) Original Image b) Regional Maxima of the image



a) Original Image b) Superimposed on original image

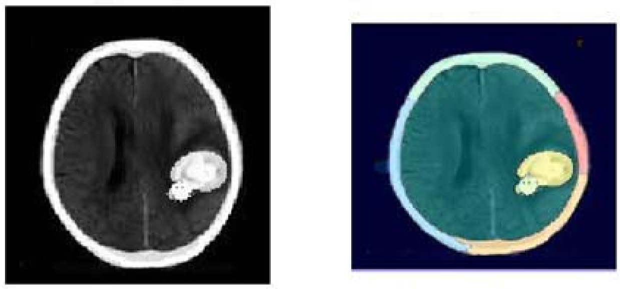
Fig. 8: a) Original Image b) Superimposed the previous image

a) Original Image b) Opening-closing by reconstruction

Fig. 9: a) Original Image b) Opening-Closing by reconstruction- Morphological Operation

E Segmentation

Watershed transforms works for images even with low contrast. Thus it helps in separating out the distinct regions. The watershed transform is computed on the gradient of the original image, so that the catchments basin boundaries are located at high gradient points.



a) Original Image b) Segmented Image

Fig. 9: a) Original Image b) Segmented Image

F Feature Extraction

After segmentation, we extract certain features of the image and input it further to a classifier. Thus main aim of this feature extraction is to reduce the original datasets by measuring certain features. The classifier used is a GLCM (Grey Level Co-occurrence Matrix). The GLCM functions characterize the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image, thus creating a GLCM, and then extracting statistical measures from this matrix. A GLCM is a matrix where the number of rows and columns is equal to the number of gray levels, G, in the image.

The following parameters are extracted from the image:

1) Number of Objects: It shows the type of hemorrhage. If N is equals to three or more than three, then the type of hemorrhage is ICH. If N is equals to two, then the type of hemorrhage is SDH. If N is equals to one, then it shows the normal brain image.
2) Area of Objects: It shows the intensity of bleeding.
3) Energy: Measure of energy content in the image.
4) Entropy: Entropy is a statistical measure of randomness that can be used to characterize the texture of the input image
5) Covariance
6) Standard Deviation
7) Hemorrhage Percentage:
   [(object area) / (256*256)] *100

TABLE 1. : Feature Extraction Parameters

ORIGINAL IMAGE	GLCM FEATURES						
	No. of Object	Area of object	Energy	Entropy	Std Dev.	Covariance	Hemorrhage %
	3	1817	0.73726	0.59805	0.48404	0.1144	2.7725

G Classifier

Artificial Neural Network (ANN) is used for classification. It is capable of capturing and also representing input output relationship in the network. Thus it is a computational model based on structure and function of animal's nervous system, in particular brain which is capable of machine learning and pattern recognition. ANNs are represented as system of interconnected neurons which exchange information between each other. The neurons have two modes of operation: The training/learning mode and the using/testing mode. In ANN, feed forward back propagation network is used and therefore the accuracy of result is more. In the training phase of this system, six input images were taken from a given location; to extract input features and the known output will be found by naming the images from the type of hemorrhage. Then the net file can be generated using a train tool for the first time after going through few testing iterations by providing the saved input and output files. Once the input features are calculated and the vector is created, to add the image to train, the output will be defined according to the value that has been received as the output result. Once the input and output files are saved, system can be trained with them. This logic can be used to train the tested images as well.

V. RESULTS

Thus by using neural network, we can classify the hemorrhages as ICH, SDH or a normal brain image.

TABLE 2: Output of the Classifier

Original image	DETECTION		
	TYPE	NEURAL NETWORK OUTPUT	ERROR
	ICH	3	0.47838

During training, features are extracted from images. After training is completed, the trained networks are stored to be used in algorithm. Whenever an image is taken as input in the algorithm, it is simulated with trained network and goes for testing the data. All the images are tested by the proposed system.

CONCLUSION

Detecting the type of hemorrhage is a very crucial step, in a medical treatment to save life of the patient. Automatic detection of hemorrhage is a very complex task. The segmentation of the images using watershed algorithm smoothens the image. Before application of the watershed algorithm, morphological operations are performed to compute the foreground and background markers. The use of feed-forward network with back propagation has helped in reducing error at the output, thus detecting the hemorrhage efficiently. Even non technical users will find this concept useful since this system is implemented using GUI (Graphical User Interface), thus making the system easier to operate. This work is better from previous because by using proposed method user can easily classify the type of hemorrhage, its percentage as well as get information on the hemorrhage area, texture and bleeding in the hemorrhage. Thus as per result, it is clear that proposed method is best suitable for ICH and SDH type of hemorrhages.

References

[1] U. Balasooriya and M. U. S. Perera, "Intelligent Brain Hemorrhage Diagnosis Using Artificial Neural Networks", IEEE Business, Engineering and Industrial Applications Colloquium (BEIAC), 2012.

[2] Ganesan, R., Radhakrishnan, S. [2009]. Segmentation of Computed Tomography Brain Images Using Genetic Algorithm. International Journal of Soft Computing, 4[4], 157-161.

[3] Prastawa et al. [2003]. A brain tumor segmentation framework based on outlier detection. Medical Image Analysis 8, p275-283.

[4] Loncaric and Kovacevic, [1997]. Quantitative intracerebral brain hemorrhage analysis.

[5] Liu et al. [2009]. Hemorrhage Slices Detection in Brain CT Images. In Pattern Recognition, 2008. ICPR 2008. 19th International Conference on. Tampa, FL , 23 January 2009. IEEE. 1-4.

[6] Myat Mon Kyaw, [2013]. Computer Aided Detection system For Hemorrhage Contained Region. International Journal of Computational Science and Information Technology (IJCSITY).

[7] Alyaa Hussein Ali, Shahad Imad Abdulsalam, Ihsaan Subhi Nema [2015]. Detection And Segmentation of Hemorrhage stroke Using Textural Analysis on Brain CT images. International Journal of Soft Computing and Enginneering (IJSCE), ISSN: 2231-2307.

[8] Vishal R. Shelke, Rajesh A. Rajwade, Dr. Mayur Kulkarni [2013]. Intelligent Acute Brain Hemorrhage Diagnosis System. Proc. Of Int. conf. on Advances in Computer Science, AETACS.

[9] Ying Z.,R.Naidu and C.R. Crowford, 2006. Dual Energy Computed Tomography For Exclusive Detection. J. X–Ray Sci. Technol.,14: 235-256.

[10] Mayank Chawla et. Al., A Method for Automatic Detection and Classification of Stroke from Brain CT Images. 31st Annual International Conference of the IEEE EMBS, Minneapolis, Minnesita, USA, Sepember 2009.

[11] Mahmoud Ai-Ayyoub, Duaa Alawad, Khaldun Al-Darabsah and Inad Aljarrah, 2013. Automatic Detection and Classification of Brain Hemorrhages. WSEAS Transactions on Computers, E-ISSN: 2224-2872, October 2013.

[12] C. Amutha Devi and Dr. S. P. Rajagopalan [2013]. Brain Stroke Classification Based on Multilayer Perceptron Using Watershed Segment and Gabor Filter. Journal of Theoretical and Applied Information Technology, ISSN: 1992-8645.

[13] Anju Bala, An Improved Watershed Image Segmentation Technique using MATLAB. International Journal of Scientific and Enginnering Research, Volume 3; Issue 6, June 2012.

[14] Fatima, Sridevi M., Saba Naaz and Kauser Anjum, [2015]. Diagnosis and Classification of Brain Hemorrhage Using CAD System. NCRIET-2015 and Indian J. Sci. Res. 12(1): 121-125,2015.

[15] T. Gong, R. Liu, C. L. Tan, N. Farzad, C. K. Lee, B. C. Pang, Q. Tian, S. Tang and Z. Zhang. Classification of CT Brain Images of Head Trauma. In Proceedings of the 2nd IAPR international conference on Pattern Recgnition In Bioinformatics, PRIB'07, pages 401-408,2007.

[16] D. Kailash Kharat, Pradyumna and M. B. Nagori. Brain Tumor Classification Using Neural Network Based Methods, Internaional Journal of Computer Science and Informatics. ISSN (PRINT): 2231-5292, Vol-1, Iss-4,2012.

[17] D. Pham and C. Xu and J. L. Prince, "A Survey of Current Methods in Medical Image Segmentation", Annual Review of Biomedical Engineering,1998.