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RESEARCH ARTICLE

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DIAGNOSIS OF BRAIN HEMORRHAGE BY USING ARTIFICIAL NEURAL NETWORKS

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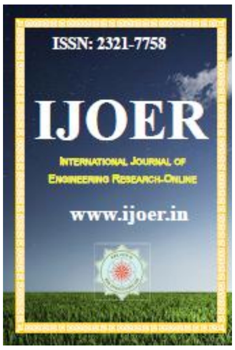


ABSTRACT

Brain hemorrhage is a type of stroke, which occurs due to artery bursting in the brain, causing bleeding in the surrounded tissues. Diagnosing brain hemorrhage, which is mainly through the examination of a CT scan enables the accurate prediction of disease and the extraction of reliable and robust measurement for patients in order to describe the morphological changes in the brain as the recovery progresses. The aim of this project is to help radiologist as well as medical students in diagnosis of brain hemorrhage in more refined manner by feeding CT images & identify the type of brain hemorrhage using watershed algorithm along with artificial neural network.

Keywords - Computed tomography (CT), Artificial Neural Networks (ANN), Back Propagation Network (BPN), Gray Level Co-occurrence Matrix (GLCM).

I. INTRODUCTION

This Brain hemorrhage is a type of stroke, which occurs due to artery bursting in the brain, causing bleeding in the surrounded tissues. The symptoms of brain hemorrhage are a sudden severe headache, Weakness in an arm or leg, nausea or vomiting, changes in vision, difficulty in speaking or understanding speech, difficulty in swallowing, loss of balance etc. The major risk factors for causing brain hemorrhage are head trauma, high blood pressure (hypertension), diabetes, smoking habits, alcohol usage, aneurysm, blood disorders like hemophilia, sickle cell anemia etc. The other factor associated with higher risk of stroke includes personal or family history of stroke, heart attack or transient ischemic attack. Approximately more than 80% of people who are being born with weak spots in their major brain arteries are at the risk of brain hemorrhage [1]. When blood from trauma irritates the brain tissues, it develops swelling that is cerebral edema. This edema pooled blood from surrounding tissues and accumulates to form a mass known as hematoma in brain. This will results in increasing pressure on brain tissues, thus decreases the vital blood flow and kills brain cells. Bleeding may occur inside the brain or in between brain and its covering membranes or in between layers of covering. Brain consists of two parts mainly one is upper part which is closed inside the cranial cavity called as skull and another is its elongation called as spinal cord. Spinal cord is the posterior extension of brain. It is enclosed in a neural canal of vertebral column. Thus the brain and spinal cord collectively forms central nervous system of human body. The brain and spinal cord are surrounded by connective tissue membranes called meninges.

As per bleeding in the brain, the brain hemorrhage is categorized as:

Intracerebral hemorrhage (ICH): ICH can occur close to the surface or in deep areas of the brain. Sometimes deep hemorrhages can expand into the ventricles – the fluid filled spaces in the center of the brain.

Subdural hemorrhage (SDH): Subdural hemorrhage (SDH) is a collection of blood accumulating in the potential space between the dura and arachnoid mater of the meninges around the brain.

Extradural hemorrhage (EDH): An extradural hemorrhage **(EDH),** also known as an **epidural hemorrhage,** is bleeding between the inside of the skull and the outer covering of the brain (called the "dura").

Subarachnoid hemorrhage (SAH): Subarachnoid hemorrhage (SAH) is a serious, life-threatening type of stroke caused by bleeding into the space surrounding the brain.

The main technique which helps in diagnosis of brain hemorrhages in human being is through Computed Tomography (CT) scan. CT scan is combination of x-rays. During CT imaging an x-ray tube rotates around the patient's head which captures multiple images. This captured images are analyze through computer. CT image allows radiologist and other physicians to identify internal structure of body mass, also observed its shape, size, density and texture. CT scan technique is suitable for claustrophobic patients as well as those patients having metallic or electrical implants in their body. It is also suitable for these who are too large in size. CT scan is effective in diagnosing bleeding and fractures in inner parts of body.

The objective of this project is to develop and evaluate convenient, intelligent and accurate system of hemorrhage detection. This proposed system enables users like radiologist or medical students as well as doctors to diagnose hemorrhage and specify the exact type of hemorrhage if one exists using Watershed Algorithm along with neural network for hemorrhage classification by feeding CT images.

II. RELATED RESEARCH

In each year, brain hemorrhages are affecting 220 people out of every 100000 in Asia while 7 people out of every 100000 in West [1]. The statistical data shows that women are affected more than men by ratio of 3:2.

R. Ganesan had proposed segmentation of CT brain image using Genetic Algorithm. In study, original images are enhanced by using Selective Median Filter and the Genetic Algorithm is used to segment image [2].

Several computer aided methods have been came for segmentation and quantification of brain tumors ranging from manual or user-assisted outlining performed by medical expert to fully automatic methods. Prastawa et al. has presented a approach for automatic segmentation of tumors and adjoining edema from non-enhancing multichannel MRI [3].

Loncaric et al. described a method for quantitative analysis of CT images, in particular for determining volume of Intracerebral brain hemorrhage (ICH) which is based on fuzzy clustering, expert system labeling and enables automatic determination of volume of ICH region [4].

Myat Mon Kyaw introduced an automated method for detection and classification of an abnormality (hemorrhage) or stroke in brain CT images [6].

Vishal R. Shelke presented an approach for classification of intracranial hemorrhage. In study, the image enhancement tools and medical filtering was used. The thresholding technique is used to separate out suspicious hemorrhagic region of interest (ROI). The various morphological operations are applied before hemorrhage detection to get to get uniform ROI. Geometrical and textural features used as input to neural network and support vector machine (SVM). This algorithm is tested on different classifiers like support vector machine and neural network [8].

C. Amutha Devi has proposed a method for classifying the brain MRI images into stroke and non-stroke images. This method extracts features from MRI images of brain using watershed segmentation and Gabor filter [12].

III. PROPOSED METHODOLOGY

The framework of proposed algorithm dataflow is depicted in Fig. 1.

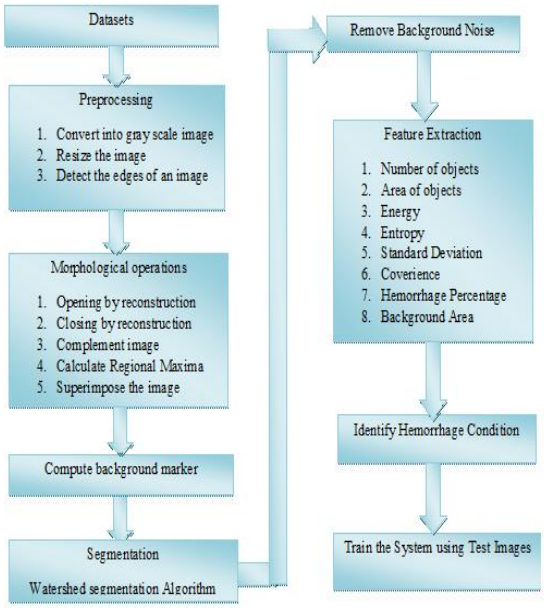
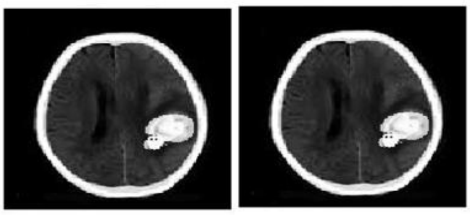


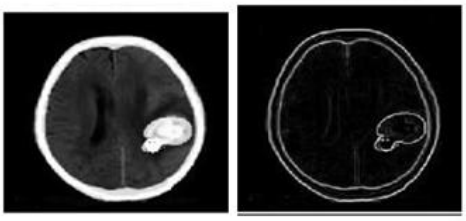
Figure 1: Flow Chart of Process

A. *Datasets:* The dataset consists of 45 CT images of human brain. These images include 18 images of ICH, 8 of SDH and 19 normal images. In this study, CT images are used for diagnosis of brain haemorrhage. CT scan is able to image bone, soft tissues and blood vessels all at the same time. CT images are read first. Then brain CT image is converted into jpeg. This image will be uploaded to the system for pre-processing.

B. *Pre-processing:* Preprocessing is used to improve the quality of an image. In this study, preprocessing techniques are developed to remove skull portion surrounding the tissues. In preprocessing, first we convert the image into gray scale image to make it contrast. After conversion, resize the image to 256 pixels by 256 pixels size so as to it fits on system user interface and then convert into two dimensional image.



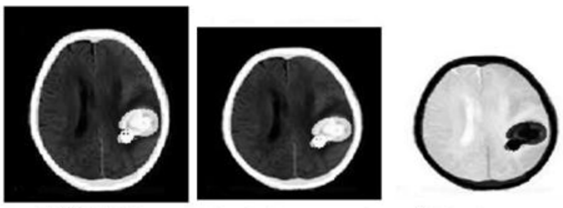
a) Original Image b) Gray Scale Image



c) Resized Image d) Edge detected Image

Figure 2: Preprocessing

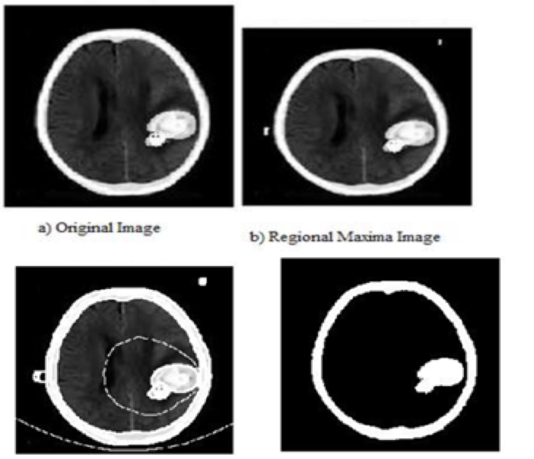
C. *Morphological Operations:* Morphology is related to shape, size and structure of an object. Morphological operations can also be applied to gray scale images such that their light transfer functions are unknown and therefore their absolute pixel values are of no or little interest. Morphological operation depends only on the relative ordering of pixel values, not on their numerical values. Some of mathematical morphological operators are as dilation, erosion, 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. In this case the structuring element is often called a probe, because it is probing the image looking for small objects to filter out of the image. Closing consists of a dilation followed by erosion and can be used to fill in holes and small gaps.



a) Original Image b) Opening by reconstruction c) Closing by reconstruction

Figure 3: Opening and closing by reconstruction

After opening and closing reconstruction operation, we are taken the complement of gray scale image 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.



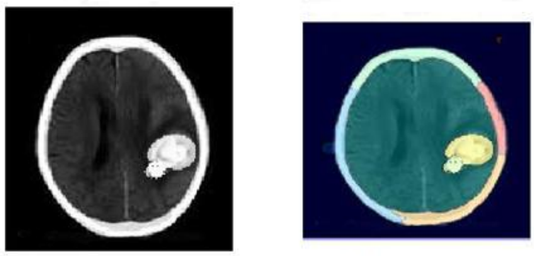
a) Original Image b) Regional Maxima Image

c) Superimposed on original image d) Opening-closing by reconstruction

Figure 4: Regional maxima, superimposition and background marker image

D. *Segmentation of Pre-processed Image:* Segmentation is very important in medical image analysis. Exact location of required objects and boundaries in images is done through image segmentation. Image segmentation is a process of partitioning the image into non-intersecting regions, so that each region is homogeneous. Pixels in a region are similar according to some homogeneity criteria such as colour, intensity or textures, so as to locate and identify objects and boundaries in an image. After preprocessing, the image will be segmented to identify required objects in CT scan and to extract values needed as input. In this study, I used watershed segmentation algorithm. The goal of watershed segmentation algorithm is to find the “watershed line" in an image in order to separate the distinct regions.

The drawback of watershed algorithm is over-segmentation. An approach based on concept of marker is used for resolving the over-segmentation problem. A marker is a connected component belonging to an image. The markers include the internal markers, associated with objects of interest, and the external markers, associated with the back-ground.



a) Original Image b) Segmented Image

Figure 5: Segmentation

E. ***Feature Extraction:*** After segmentation of preprocessed image, we extract required information. Feature is said to be characteristics that describes whole image. It can also refer as an vital piece of information which is essential for computational task related to specific applications. Feature extraction is the process by which certain features of interest within an image are detected and represented for further processing. Feature extraction is the method of capturing visual content of an image. The goal of feature extraction is to reduce original datasets by measuring certain features. In this study, I used grey level co-occurrence matrix (GLCM) for feature extraction. GLCM is statistical method of extracting textural features from images. The GLCM is form by grey scale image. The GLCM function is characterized texture of an image by calculating how often pairs of pixels with specific values and in specified spatial relationship occurred in an image creating GLCM and then extracting statistical measure from this matrix. The extracted features by using GLCM are as:

Number of Objects: The number of objects shows the type of hemorrhage.

Area of Objects: Area of objects shows the intensity of bleeding.

Energy: is a measure of unorderedness or information content in an image.

Energy = $\sum_i \sum_j \{p(i,j)\}^2$ (1)

Entropy: Entropy is a statistical measure of randomness that can be used to characterize the texture of the input image.

Entropy = $-\sum_i \sum_j p(i,j) \log(p(i,j))$ (2)

Standard Deviation: Angular second moment is called as standard deviation.

Standard Deviation = $\left\{\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^2\right\}^{\frac{1}{2}}$ (3)

Where,

$$\overline{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$$

Covariance:

Covariance= $\sum_i \sum_j \{(ij)\, p(i,j) - \mu_x \mu_y\}/\sigma_x \sigma_y$ (4)

Where, μ_x, μ_y, σ_x and σ_y are standard deviations of p_x and p_y.

Hemorrhage Percentage: The hemorrhage percentage is calculated by,

Hemorrhage percentage = $\frac{(\text{object area})}{(256*256)} * 100$ (5)

These parameters are enlisted for various images in following Tables:

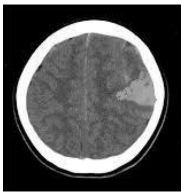


Fig 6: CT image of ICH Fig 7: CT image of SDH

Table 1: Values of extracted features for fig 6.

Parameters	Values
No. of objects	3
Area of object	1817
Energy	0.73726
Entropy	0.59805
Standard Deviation	0.48404
Covariance	0.1144
Hemorrhage Percentage	2.7725

Table 2: Values of extracted features for fig 7.

Parameters	Values
No. of objects	2
Area of object	11130
Energy	0.70323
Entropy	0.65822
Standard Deviation	0.49054
Covariance	0.13099
Hemorrhage Percentage	16.983

Fig 8: Normal CT image

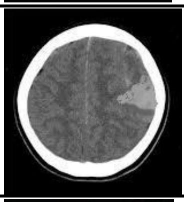
Table 3: Values of extracted features for fig 8.

Parameters	Values
No. of objects	1
Area of object	0
Energy	0.79488
Entropy	0.4926
Standard Deviation	0.50098
Covariance	0.08593
Hemorrhage Percentage	0

F. *Classifier:* Extracted features are acts as input to neural network classifier. Neural network is able to capture and represent input output relationship. An artificial neural network (ANN) is a computational model based on structure and function of animal 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. This system uses feed forward back propagation neural network which has 8 input nodes, 1 hidden layer with 20 neurons and 1 output layer. Feed-forward networks commonly use the Back propagation (supervised) learning algorithm to dynamically alter the weight and bias values for each neuron in the network. Back propagation uses target values to calculate error function of artificial neural network. The networks associated with back propagation learning algorithm are called as Back Propagation learning Networks (BPNs). For given set of training input output pair, this algorithm provides procedure for changing weights in BPNs to classify input correctly. The classification process is divided into two phases as training phase and testing phase. During training phase, 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.

IV. Results and Discussion

By using neural network we can detect the type of hemorrhage whether it is ICH, SDH or normal image. It will be helpful for doctors as well as medical students for better diagnosis and treatment. The result of the system using neural network for an image is enlisted in following table:

Sr. No.	Original Image	Detection		
		Type	Neural Network Output	Error
1.		ICH	3	0.4783
2.		SDH	2	-0.011
3.		Normal	1	-0.031

The dataset consists of 45 CT images of human brain which includes 18 images of ICH, 8 images of SDH and 19 images of normal images. Out of these images, 6 images are trained. 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 these images are tested by the proposed system. During testing, 18 images are detected as ICH, 8 images as SDH and 19 images as normal images. But by observation, 9 images are ICH, 5 images are SDH and 10 images are normal. After testing, the proposed system gives 50% accuracy for ICH, 62% for SDH and 52% for normal images.

IV. CONCLUSION

Detecting the exact type of hemorrhage is important in the medical diagnosis and treatment of the patient. The use of watershed algorithm along with neural network enables the user to classify hemorrhage type from fed CT image. It was found that boundaries of each region are continuous, but problem of over-segmentation was faced as well as the process was little bit time consuming. An approach based on the concept of marker is used for resolving the over-segmentation problem in the watershed algorithm. The use of feed-forward network using with back propagation has reduced the error at the output and which enables to detect the hemorrhage effectively, thus by using proposed method user can identify the type of hemorrhage. As per result it is clear that proposed method is best suitable for ICH and SDH.

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