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Identification of Haemorrhage in Brain MRI Using Segmentation Techniques

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Abstract: **- Image processing techniques help in clearly identifying, segmenting and bringing out the possible outcome in the field of medical diagnosis. Haemorrhage in the brain prevailing due to mental stress and trauma is the most important cause of illness and death. Identifying the injured region from the normal-unaffected part of the brain has to be done such that there are no false predictions at the time of emergency situations. Segmentation is an approach to extract the features of haemorrhage from brain MRI dataset. Image Processing techniques; initially pre-processing steps, morphological operations, and segmentation operations are being deployed to highlight the haemorrhage area. In this paper, in Pre-processing; median filter is used to preserve the edges, morphological operations such as erosion-dilation removes and adds pixels to the boundaries of objects in the image, segmentation technique like Otsu thresholding looks onto the region or area inside the segment that has to be brought out and Watershed Segmentation helps in marking foreground and background location of object in image. This concludes that segmentation of haemorrhage in the brain can be done distinctly. Accuracy rate in segmentation is compared to get the best suitable segmentation algorithm.**

Keywords**: Brain Haemorrhage, Filtering, Morphological operations, Otsu Thresholding, Watershed Segmentation.**

I. INTRODUCTION

Brain constitutes the most essential part of the nervous system. Cerebral vascular diseases such as haemorrhage, stroke, is an important health tragedy worldwide and it affects 16 million people among the total population every year. About 30% of individuals that have a haemorrhage and stroke die and 40% remain with serious physical restrictions.[13] Though, progress in the damaged region is possible if treatment is performed without delay. Haemorrhage is an emergency problem for which early identification and measures are difficult; however, diagnoses using computer technology can play an important role in obtaining information unnoticeable to the human eye. Despite of the presence of factors inhibiting the coagulation of blood within vessels, clotting may occur at times.[14] Such clots frequently are formed in veins than in arteries. The blood clot or thrombus produced in the streaming blood is called thrombosis. [15] A clot in the cerebral vessel is called stroke or cerebral thrombosis. The stroke and the haemorrhage are also due to vascular malformations. Haemorrhage or bleeding of blood vessels may be due to hypertension which results in bursting of blood vessels or due to aneurysm in which the arterial wall bulges and forms a sac like structure and ruptures later on. Stroke causes both physical; and mental crippling. It is a worldwide health problem, which can occur at any age. Several risk factors may lead to stroke and brain haemorrhage, such as cardiac abnormalities, diabetes, elevated blood lipids, hypertension, obesity, smoking and stenosis (narrowing of valvular orifice), etc. Stroke may be caused due to vascular occlusion, which is a blockage in the cerebral artery. Diagnosis takes place after looking into the Computer tomography scan and Magnetic Resonance Imaging of the brain. At times, unaffected brain tissues partly cover the injured area or the Haemorrhage area, leading to false understanding in diagnosis. At the time of clinical emergency, steps should be taken immediately. In order to do so, injured areas should be separated from unaffected brain tissues. Several algorithms or techniques are employed which give immediate segmentation of the injured area from the normal unaffected area. The accuracy and time taken for segmenting the areas of haemorrhage is the efficiency of the proposed method.

II. LITERATURE REVIEW

Qingmao Hu et al.,(2005) [1] employed Fuzzy C-Means clustering to determine the threshold for head mask and the low threshold for brain segmentation. Fuzzy C-Means is beneficial than curve fitting as it does not assume the noise model and is appropriate yet in the existence of heavy noise and other elements. Here high threshold value is considered as the weighted intensity average of the boundary pixels between bones and white matter/ grey matter. The CT volume is binarized, next the brain candidates are found through distance criterion. At last the brain is identified with the help of brain mask propagation using the spatial association of neighbouring axial slices. Non-brain tissues with alike intensities (muscles and sinuses) to White Matter or Grey Matter have been effectively separated with the help of distance criterion and brain mask propagation.

Liao et al., (2009) [2] evaluated methods for segmentation of extracerebral hematomas, namely Epidural Haemorrhage and Subdural Haemorrhage. These hematomas occur outside the brain region (i.e.,) between the skull bone and the grey matter, segmenting them is a difficult task. To overcome this, the author combined Multiresolution Binary level set algorithm with image pyramids methods since differentiation is no longer required in binary level set methods and on the other hand image pyramid is an even more efficient way of computing the multiresolution variant of the binary level set method.

Bardera et al.,(2009)[3] proposed a framework to segment both the hematoma and the edema from Computer Tomography images. Framework was partitioned into two stages: the region growing approach for hematoma segmentation, the level set approach for edema segmentation. According to the research done the framework reduces the operator processing time.

Niket Amoda et al.,(2013) [4] used the watershed transformation on a gradient image which was extracted from the original image. The problem faced with the conventional intensity gradient is that it was not able to detect the interfaces between homogeneously textured image regions. Eventually this might be because the gradient image highlights the variations within the textures than showing the change between textured regions. Therefore, Texture Gradient is necessary to identify the texture boundaries. Further a marker based method is used to control the over segmentation.

Mahmoud et al.,(2013) [5] for segmentation used Otsu's method to extract the haemorrhage region from the image. In their phase, features of the region of interest were extracted followed by the classification stage where the image was classified based on the computed features of the region of interest. The results in this work showed that after pre-processing of the CT Scans, the binary classification problem solution gave 100% accuracy. Also, the suggested system achieved 92% accuracy for classifying the 3 types of haemorrhages using neural networks as a classifier.

Hema et al.,(2013) [6] proposed methodology which consisted of five phases namely, pre-processing, segmentation, tracing midline of the brain, extraction of texture features and classification respectively. In the first phase segmentation, the combination of K-means and Fuzzy c-means methods was implemented to partition the images into the binary images. From the binary images, a decision tree was then utilized to annotate the connected component into normal and abnormal regions. The average overlap metric, average precision and average recall between the results were obtained using the suggested framework and the ground truth values are 0.98, 0.99 and 0.98, respectively.

Seal et al., (2015) [7] improvised the watershed segmentation procedure. Implemented the distance transform method of watershed. The resultant image changed according to the value of the threshold. Giving the value of 4, 4 provided significant maxima in the image and are kept intact and the rest are changed.

Vijay et al., (2016) [8] used Enhanced Darwinian Particle Swarm Optimization (EDPSO) for automated tumor segmentation which overcomes the drawback of existing Particle Swarm Optimization (PSO). The method consists of four steps. First step is pre-processing using tracking algorithm to remove artifacts and unimportant areas of MRI. In the second step the noises are removed using Gaussian filter. In the Third step, segmentation was done using Darwinian Particle Swarm Optimization and in the Fourth step classification is implemented, using Adaptive Neuro Fuzzy Inference System.

Shahangian et al.,(2016)[9] after pre-processing, a modified version of Distance Regularized Level Set Evolution (MDRLSE) was implemented to detect and separate the haemorrhage regions. Then a perfect set of shape and texture features from each detected haemorrhage region were extracted. Later, a synthetic feature was applied called weighted grayscale histogram feature to select the most related features. The proposed algorithm was evaluated on a set of CT-scan images and obtained the accuracy rate of 96.15%, 95.96% and 94.87% for the segmentation of the EDH, ICH, and SDH types, respectively.

Dubey et al.,(2016)[10] systemized a rough set based intuitionistic fuzzy c-means (RIFCM) clustering algorithm for segmentation of the magnetic resonance (MR) brain images. Firstly, a new automated method was initiated to determine the initial values of cluster centroid using intuitionistic fuzzy roughness measure, achieved by considering intuitionistic fuzzy histon as upper approximation of rough set and fuzzy histogram as lower approximation of rough set. A new intuitionistic fuzzy complement function was proposed for intuitionistic fuzzy
image depiction considering the intensity inhomogeneity

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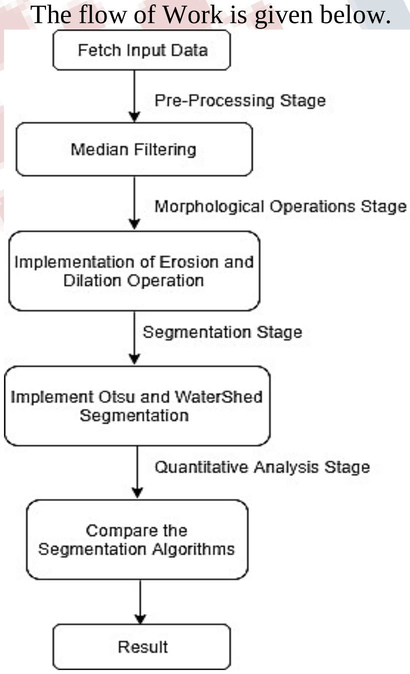
and noise in brain MR images. Pedro et al., (2017) [11] conducted a research approach to be applied to CT images to identify and classify the occurrence of stroke diseases. The significance of the results demonstrated that the Analysis of Brain Tissue Density method is a useful algorithm to extract features to support in stroke diagnosis.

Ivan et al., (2017) [12] presented Potential Field Segmentation algorithm (PFS), and also used the ensemble algorithms that combined the results generated by PFS and other methods to accomplish a fused segmentation. For the PFS method, the clustering algorithm; Potential Field Clustering, which is based on an analogy with the concept of potential field in Physics was implemented. Specifically, for each pixel in the MRI, the potential field was computed and, if smaller than an adaptive potential threshold, the pixel is associated with the tumor region. Later, evaluated the performance of the different methods, including the ensemble approaches, on the publicly available Brain Tumor Image Segmentation (BRATS) MRI benchmark database.

III. METHODOLOGY

DataSet: The dataset of brain MRI having Haemorrhage was taken for implementation. The process was implemented in Python using Jupyter Notebook.

The flow of Work is given below.



a) Pre-Processing: Intracranial matters, both the brain and cerebral spinal fluid are surrounded with spaces that should be segmented. The MRI DICOM Image with pixel value is being used. The size of the object and its corresponding pixel values should remain constant for each and every image in the database. In order to do so, the DICOM image has to be used as a direct input file for all the operations (i.e.,) it should not be converted to .jpeg or .png format. This helps in maintaining the standard quality of the image such that the pixels do not break. In the pre-processing step, Median filter is being used. Where this technique is often used to remove noise from an image or signal. Instead of simply replacing the pixel value with the mean of neighbouring pixel, it replaces it with the median of those pixels.

A 3-by-3 square kernel is applied on the input image. Median filter is selected since it is less sensitive to intense values and helpful to get rid of the outliers without dropping the sharpness of the input image. This makes more homogeneous surroundings in which deformity become more obvious.

The median of the set of numbers in A is $A[\frac{(n-1)}{2}]$ (1)

let $A[i]i = 0 \dots .(n-1)$

be a sorted array of n real numbers.

b)Morphological Operations: Morphological operations such as Erosion and Dilation are being implemented. In the Erosion process, the value of the output pixel is the minimum value of all pixels in the input pixels neighbourhood. Erosion removes or erodes pixels on object boundaries. In the Dilation process, the value of the output pixel is maximum value of all pixels in the input pixels neighbourhood. Dilation adds pixel to boundaries of object in an image.

An erosion of an image I by the structure element H is given by the set operation,

$$I \ominus H = \{ p \in \mathbb{Z}^2 \,|(p+q) \in I, \text{for every } q \in H\} \quad (2)$$

Where I is the input image, H is the structuring element.

A dilation of an image I by the structure element H is given by the set operation

$$I \oplus H = \{(p+q) \mid p \in I, q \in H \} \quad (3)$$

Where I is the input image, H is the structuring element.

c) Segmentation: Segmentation is regularly believed to be taken as the initial step in image analysis. The reason of using segmentation is that it subdivides an image into significant non-overlapping sections, which would be used for further analysis. It is expected that the sections obtain correspond to the physical parts or objects of a scene represented by the image.

i) Otsu Segmentation: Otsu Segmentation is basically an Optimal thresholding method which selects the threshold depending on the minimization of a criterion function. The criterion used in Otsu segmentation is the minimization of the within-group variance of the two groups of pixels separated by the given threshold value. Otsu thresholding method involves in iterating throughout all the potential threshold values and calculating a measure of spread for the pixel levels each side of the threshold, the pixels falling in foreground and background spreads is at its minimum.

Within class variance is calculated using:

$$\sigma^2 w = wb\, \sigma^2 + wf\sigma^2 f \qquad (4)$$

ii)Watershed Segmentation: The name watershed indicates to a ridge dividing areas or regions that are drained by different river systems. A catchment basin is the geographical region exhausting into a river or reservoir. The most important advantage using the Watershed method apart from other previously developed segmentation methods is the resultant boundaries that form closed and connected area. The boundaries of the resultant region always concur to contours which are seen in the image as noticeable contours of objects.

Let f ϵ C(D) have minima{mk}kϵI, for some index set I. The catchment basin CB(mi) of a minimum mi is defined as the set of points x ϵ D which are topographically closer to mi than to any other regional minimum mj:

CB(mi)={x ϵ D | ∀ j ϵ I \{i}:f(mi) + Tf(x,mi)<f(mj)+Tf(x,mj)} (5)

The watershed of f is the set of points which do not belong to any catchment basin:

$$Wshed(f) = D \cap \left(\bigcup_{i \in I} CB(m_i) \right)^c \qquad (6)$$

Let W be some label, W ∉ I. The watershed transform of f is a mapping λ : D → I U {W}, such that λ(p)=I if p ϵ Wshed(f). So the watershed transform of f assigns labels to the points of D, such that (i) different catchment basis are uniquely labelled, and (ii) a special label W is assigned to all points of the watershed f.

I. RESULTS AND DISCUSSION

We collected 17 cases of Haemorrhage and 10 normal cases from Billroth Hospital, Chennai. The entire key in data set used for haemorrhage detection consisted of non-enhanced 256x256 MRI brain images. The proposed approach has been evaluated on a dataset of 20 patients (250 image slices). The approach comprises of three phases. In the first phase noise is removed using median filtering. In the second phase, the haemorrhage region is segmented using Otsu and Watershed technique. In the third phase, evaluation of the performance of the algorithms using Precision and Recall Measure is carried out.

a) Quantitative analysis

The segmentation results are quantitatively estimated. A region of Haemorrhage identified by an qualified radiologist is the ground truth. Each pixel fit in to one of the four classes respectively: true positive (TP) is correctly classified as positive pixels (containing Haemorrhage); true negative (TN) is correctly classified as negative pixels; false positive (FP) is incorrectly classified as negative pixels; and false negative (FN) is incorrectly classified as positive pixels. Three quantitative measures such as precision, recall and overlap metric are used to evaluate the segmentation result.

The formulae for these are given in Eqs. (8), (9), (10) and (11). The three terms are defined as follows: Sensitivity (true positive fraction) is the probability that a diagnostic test is positive, given that the person is affected due to haemorrhage.

$$\text{Precision} = TP / TP + FP \qquad (7)$$

$$\text{Recall or Sensitivity} = TP/TP + FN \qquad (8)$$

$$\text{Overlap Metric} = 2 * TP / 2 * TP + FN \qquad (9)$$

Specificity (true negative fraction) is the probability that a diagnostic test is negative, given that the person is not affected due to haemorrhage,

$$\text{Specificity} = TP/TP + FP \qquad (10)$$

$$\text{Accuracy} = TP + TN/TP + TN + FP + FN \qquad (11)$$

Accuracy is the probability that the analytical test was accurately performed.

Table-1: Result of the Quantitative Analysis

Measures	Otsu	Watershed
Precision	0.85	0.94
Overlap Metric	0.87	0.97
Specificity(%)	85%	94%
Recall or Sensitivity(%)	89%	94%
Accuracy(%)	84%	93%

The comparative analyses of the algorithms used are given in Table 1. The results of the segmentation technique used to depict the region of interest are given in Table 2. Using the Otsu segmentation algorithm the accuracy in segmenting the region of interest was 84%. Whereas the Watershed segmentation method gave an accuracy of about 93%. Therefore Watershed is the best Segmentation algorithm for our dataset. The average overlap metric, average precision and average recalls between the results obtained using the segmentation approaches depicts that watershed gave good performance. From the images in the Results, Table (2), we can clearly see that Watershed segmentation provides a better view of the affected region.

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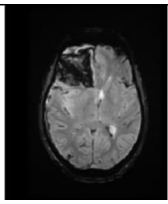
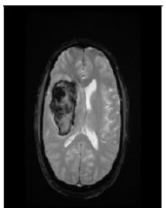
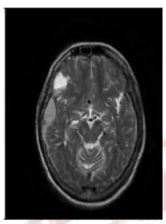
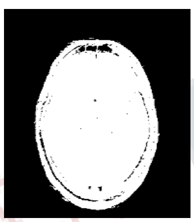
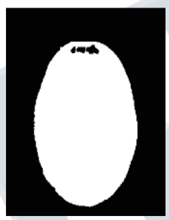
Results: Table-2: The results of the Segmentation for the corresponding input images are given below.

Original Image	Otsu Method	Watershed Method
		
		
		

Inference: From the Figure 1, we can clearly see that Watershed exactly helps in visualizing the area or region of the haemorrhage, (i.e.,) the area from where the blood has oozed out or comes out. Watershed leaves behind the other part where the blood has flowed.

V. CONCLUSION

An automatic system which is able to segment haemorrhage from brain MRI dataset using Otsu and Watershed segmentation algorithm has been done. The comparison between the two segmented algorithms on non-enhanced brain MRI dataset has been done. The system can provide a better understanding to the physicians to diagnose haemorrhage, for providing immediate treatment. The brain region containing the haemorrhage can be accurately segmented from the brain image. The average overlap metric, average precision and average recall for watershed algorithms are 0.97, 0.94 and 0.94 respectively. The proposed system helps to improve the accuracy in detection of haemorrhage and also reduces the menace of false diagnosis and false treatment.

VI. ACKNOWLEDGEMENT

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