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An Efficient Hemorrhage Detection System using Decision Tree Classifier

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Abstract: *the visual representations of the inner constituents of body along with the functions of either organs or tissues comprising its physiology are developed in medical imaging. These images can be obtained by various techniques such as computed tomography (CT), magnetic resonant imaging (MRI), and x-ray. The objective of the system mentioned in this paper is to detect the presence of hemorrhage and to classify the type of it when detected. CT images are considered here to find the hemorrhage. Pre-processing techniques such as grayscale conversion, image resizing, edge detection and sharpening are done to make the input image suitable for further processing. After preprocessing the images go through morphological operations to help identify the shape related features in correspondence to the hemorrhage. Sobel and markers are used in the processed ct image to highlight the interested region. Then watershed algorithm is employed for the purpose of segmentation. The presence of hemorrhage can be detected as a result of segmentation. Once hemorrhage is detected feature extraction is done to classify its type. Active contours are drawn and features extracted are fed to the decision tree. The classifier helps in finding the type of hemorrhage with the detected features. The classifier result can be viewed, interpreted and evaluated by medical assistance. The aim of this research is to increase the chance of predicting hemorrhage in the image and then to classify its type. The proposed system classifies three types of hemorrhages. The average accuracy of the system in classifying the three types of hemorrhage is found as 98%*

Keywords: *watershed segmentation, active contours, decision tree, hemorrhage*

I. INTRODUCTION

A brain hemorrhage is a particular type of stroke which is caused as a result of bleeding due to the result of a ruptured artery or some other reason such as sudden movement of the brain resulted as an accident. The nearby tissues are affected because of the pooling of blood on rupture. This accumulation of blood is referred to as hematoma. Trauma and high blood pressure are found to be the main sources for hemorrhage.

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The severity of hemorrhage depends on the extent of bleeding. Based on this immediate medical assistance is required. The visual representations of the organs and tissues of the brain are found using medical imaging techniques. These imaging technologies help in diagnosing them accurately. These medical images acquired by any of the techniques such as MRI, CT require further processing to predict exactly the presence of hemorrhage. Hemorrhage in CT images can be categorized into many types [1]. The following are aimed for classification in this system.

Intra Cerebral Hemorrhage (ICH): This type of hemorrhage occurs in the deep or inner parts of the brain and can penetrate into the fluid filled spaces in brain.

Sub Dural Hemorrhage (SDH): Occurs outside the brain due to an injury. When the blood vessels in between the brain and Dura burst it causes this type of hemorrhage.

Sub Arachnoid Hemorrhage (SAH): The type of hemorrhage where it bleeds in the surrounding of the brain is said to be SAH.

The proposed system employs CT scanned images [2]. The tissues inside the brainare scanned at varying levels of intensity. The unwanted noises are removed by pre-processing the input CT image. The unwanted distortions are removed by a sequence of operations. Further the image is enhanced thereby making it suitable for further processing. The structuring element of the image (hemorrhage) is altered by series of shape related operations called morphological operations. This also helps in removing unwanted features and other imperfections related to morphology. Erosion and dilation are the commonlyused operationsfor this purpose in medical imaging.Then watershed algorithm is employed for segmenting the image. The technique of dividing the image into multiple segments is known as segmentation. After segmentation it is easy to process the analyzed region of interest. The presence of hemorrhage can be detected with watershed algorithm. The features can be extracted using various methods such as Grey Level Co-occurrence matrix (GLCM), Active contours etc. In this system contours are drawn and features are fed into a Decision Tree classifier to find the type of hemorrhage.

II. LITERATURE SURVEY

C. Amutha Devi et al proposed “Brain Stroke Classification Based on MultiLayer Perceptron Using Watershed Segmentation and Gabor Filter” which contributed for identifying positive and negative stroke in MRI images [3]. Feature extraction is done using Watershed segmentation and Gabor filter [4].

Multilayer Perceptron (MLP) is used for classification based on the extracted features. By varying the features experiments were conducted to find the accuracy of the system. Sigmoidal function with less root mean square error achieves best classification performance.
Maryam Taghizadeh Dehkordi proposed a new energy function for tumor segmentation using level set method [5]. A Gaussian filter is applied to find if the pixel belongs to tumor region. The tumor features are introduced into the energy function and new contour model was designed.
Nandhini V and Karthick G proposed a methodology to detect tumors. MRI imagesand clustering algorithms were tested [6]. A cluster is a group of members where all the members in certain group aredefined by similar characteristics. In the proposed system [7]K-means clustering algorithm is used for segmentation of the image followed by morphological filtering for tumor detection. Noise present in images, are removed using a filter. Due to the presence of mis-clustered regions followed by K-means clustering algorithm, morphological filtering is done to detect and eliminate them. The unwanted shape oriented features are removed using morphology operations. PNN (Probabilistic Neural Network) algorithm based classifier is used.
B. Shanmugapriya et al proposed a method to segment the brain tumor using Support Vector Machine (SVM) classifier [8]. Features are extracted from the training dataset. With the help of training feature vector SVM model is created and segmentation is done. The test images are compared to the trained set and then segmented. Polynomial and Gaussian RBF kernels are both compared and RBF is found accurate.

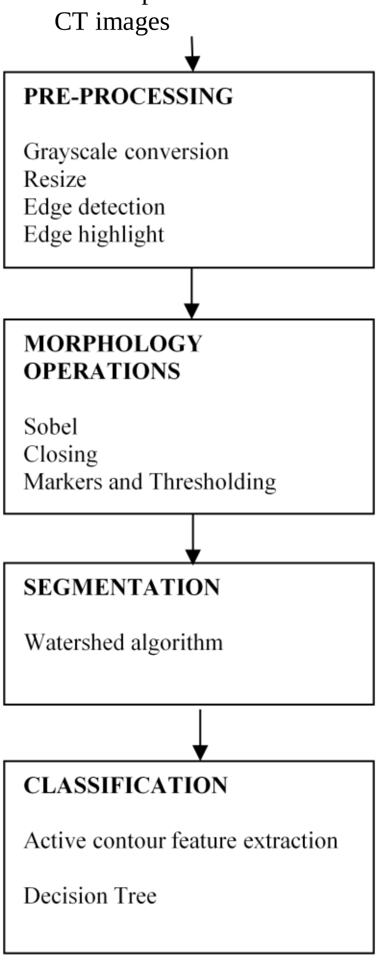

Figure .1 System Flow

Sinachettra Thay et al proposed "Fast Hemorrhage Detection in Brain CT Scan Slices Using Projection Profile Based Decision Tree" contributes for the detection of hemorrhage using CT scan slices[9]. A fast and accurate method to detect hemorrhage using decision tree is used here. Based on the features extracted decision tree is employed for both images with and without hemorrhage. Features related to intensity and other parameters are considered. This system has a classification accuracy of 99% and detection time of 0.12 second.
D. Vijayakumar and V.V. Jaya Rama Krishniah proposed an automated framework to detect hemorrhage using decision tree classifier [10]. Stroke and hemorrhage are both classified with accuracy of 91% and 93% respectively. A typical tree structure with root splitting into further nodes is employed. Regions are grouped distinctly and thereby region of interest can be found easily. Once the region is found it is easy to classify based on their features.

III. PROPOSED METHODOLOGY

The input CT images are first pre-processed.Grayscale conversion, image resizing, edge detection and edge sharpening are some of the pre-processing steps that are involved here.Then a set of operations such as sobel, closing, markers and thresholding are done and these are the shape related morphology operations. Watershed algorithm is employed to segment the image and to find the required region of interest. The proposed system (Fig 1) also aims at classification of hemorrhage once detected as a result of segmentation. Feature extraction is done by drawing the contours and these features are fed into a decision tree for classification.

3.1 DATASETS

200 CT images of human brain are considered of which 150 images contain hemorrhage and rest without hemorrhage.

3.2 PRE-PROCESSING

The unwanted portions and noise from the scanned CT image are removed so that the quality of input is improved and enhanced. (Fig 2)

i. Grayscale conversion

The input scanned image is converted to grayscale. This makes it suitable in extracting the exact needed information. The colors are eliminated and it highlights any abnormalities that are present in the image.

ii. Resizing

Resizing is done to convert the input images to a specified size so that it satisfies several constraints. The resolution of display devices is not the same as resolution of scanned images. They vary in size and other dimensions. Therefore to make it a constant, the grayscale image is resized to certain specifications. Here the grayscale images are resized into 256x256 pixels.

iii. Edge detection

The process of detecting edges to determine the boundary of hemorrhage and boundary of brain is known as edge detection. Canny edge detector with Gaussian filter is used to detect the edges from the resized image. Canny algorithm is a multistage edge detection algorithm with the following steps. Gaussian filter is applied. This smoothens the image for the noise removal. Then the intensity gradients of the image are calculated with gray values.

Non-maximum suppression is done next. The spurious responses are being eliminated. Then double thresholding is done to find the potential edges. Then finally all edges that are weak and not connected to strong edges are suppressed to find the final set of edges.

iv. Edge sharpening

The boundaries of object surfaces are made contrasting to render the image suitable for morphology process and segmentation. These boundaries are the highlighted edges.

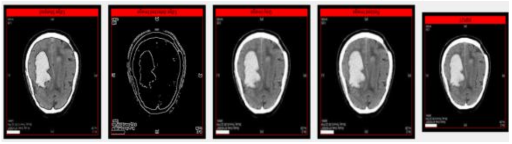

Figure .2 Pre-processing Stage

3.3 MORPHOLOGICAL OPERATIONS

Morphological operations are aimed to remove imperfections by applying shape related operations. (Fig 3)

i. The gradients of the image are used to find the elevation map from the edge image of previous phase. Sobel operators are used for this purpose.

ii. After sobel, closing reconstruction is performed. A dual operation that performs dilation followed by erosion is known as closing. The process of dilating the pixels such that the small holes on the object and the foreground can be filled is said to be dilation. Closing reconstruction is considered essential before segmenting the image. Erosion is the process of eroding to remove unwanted pixel noise.

iii. To find the background imagemarkers are used. The extreme parts of the histograms comprising the gray values are used to find those markers.

iv. Binary thresholding is done to remove the unwanted highlighted regions from the Sobel image. This can be done with superimposing marker and Sobel image.

3.4 SEGMENTATION

Segmentation is the technique that involves the partitioning of image into multiple segments. To locate the required region of interest the image from previous phase is broken down into segments. Watershed segmentation a most commonly used algorithm for medical image processing is used here. The image can be viewed as geological landscape and the watershed lines are used to determine boundaries that separate image regions. The watershed transform computes catchment basins and ridgelines the so called watershed lines and the catchment basins correspond to the regions and ridgelines relating to region boundaries. The foreground pixels are identified from the threshold image as the maximum values from the watershed lines. Here these lines represent the boundaries of hemorrhage. The presence of hemorrhage is found at the end of segmentation by superimposing the foreground image on the background grey image (Fig 4).

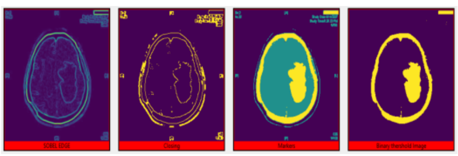

Figure 3Morphology Operations

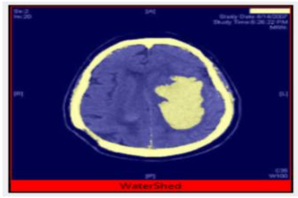

Figure 4 Watershed output

3.5 FEATURE EXTRACTION

Feature extraction is the process of reducing the number of constraints that are needed for representing the original data in an informative way. Segmented image is considered to draw the contour. In general the gray pixel values of hemorrhage will lie in the range 180-240. The algorithm considers the region of interest by making the range values as the threshold using the kernel check method from segmented image. 3x3 kernel is built to compare the neighboring pixels with the threshold and mark or unmark the region as “Region of Hemorrhage” and contour is drawn. From the contour the following features are extracted and considered.

i. Moments
ii. Contour area
iii. Contour perimeter
iv. Contour approximation
v. Convex hull

Moments help in calculating the area and centre of mass of the object.

3.6 CLASSIFICATION

Decision tree classifier is used to find the type of hemorrhage. Starting from the root node, the tree branches as a hierarchy and ends with leaf nodes. The extracted features are considered and fed into the classifier to find the type of hemorrhage. A sample output is displayed in Fig 5.

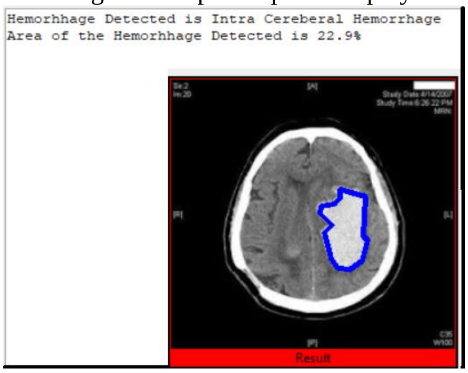

Figure 5 Sample Output

IV. PERFORMANCE ANALYSIS

A dataset of 150 images provided by Dr. Divyan Paul, Ministry of Health Hospital (Muscat) are considered in evaluating the efficiency of the proposed system. 150 of them are positive stroke images (with hemorrhage). Experiments were conducted using watershed segmentation and decision tree classifier and the following results were obtained. Of the 150 stroke images each 50 belongs to ICH, SDH and SAH.

Table I Classification of ICH

Result		Predicted value	
		Predicted Positive	Predicted Negative
Actual value	Actual Positive	TP = 50	FN = 0
	Actual Negative	FP = 1	TN = 49

After the calculation of the table values their corresponding rates are found using the formula as follows

Accuracy rate

ACC = (TP+TN) / (TP+FN+FP+TN) (1)

Sensitivity

S = TP/ (TP+FN) (2)

Precision

P = TP/ (FP+TP) (3)

Specificity

SP = TN/ (FP+TN) (4)

Where TP, FP, FN, TN represent True Positive, False Positive, False Negative and True Negative correspondingly. The accuracy rate of classification for each type can be calculated using the formulae specified. The values from Table I, Table II, and Table III are considered to find the accuracy.

Table II Classification of SDH

Result		Predicted value	
		Predicted Positive	Predicted Negative
Actual value	Actual Positive	TP = 49	FN = 1
	Actual Negative	FP = 2	TN = 48

100 images with 50 positive strokes of a particular type and 50 of other type along with negative stroke images are considered for each case.

Table III Classification of SAH

Result		Predicted value	
		Predicted Positive	Predicted Negative
Actual value	Actual Positive	TP = 50	FN = 0
	Actual Negative	FP = 1	TN = 49

The accuracy rate of classifying ICH, SDH, SAH are found as 99%, 97% and 99% respectively. Table IV represents the measures and values of each type of hemorrhage.

Table IV Efficiency Measures

Type	Accuracy (In %)	Sensitivity (In %)	Precision (In %)	Specificity (In %)
ICH	99	100	98	98
SDH	97	98	96	96
SAH	99	100	98	98

The average accuracy of the system that classifies all three types of hemorrhage is 98%

V. CONCLUSION AND FUTUREWORK

The system is successfully trained with brain CT images and classification has been done if hemorrhage is detected. The problem of over-segmentation has been overcome by using watershed algorithm along with markers. After segmentation with the extracted contour features, decision tree classifier is employed. CT images with and without hemorrhages are considered. The overall classification accuracy is found to be 99%, 97% and 99% for ICH, SDH and SAH respectively. As an extension to this research, other classifiers can be used and their accuracies can be compared to get an efficient result. This work can also be carried on for the diagnosis of similar such medical emergencies by using other feature extraction techniques accordingly.

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