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Intelligent Acute Brain Hemorrhage Diagnosis System

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***Abstract*— The aim of this paper is to help radiologists in the prognosis of the brain hemorrhage. A novel approach to classify intracranial hemorrhage into three type's viz. Epidural Hemorrhage (EDH), Subdural Hemorrhage (SDH), Hypertensive bleed (HTN) has been presented here. In order to ease the classification, image enhancement tools and median filtering was used. Further, unique thresholding technique is used to separate out the suspicious hemorrhagic Region of interest (ROI). Before hemorrhage detection, various morphological operations are applied to get a uniform ROI. Geometrical and textural features are used as inputs to Neural Network (NN) and Support Vector Machine (SVM). Application of NN and SVM yielded 0.875 recall, 0.952 precision and 0.958 recall, 0.98 precision respectively.**

***Index Terms*— CT image, intracranial hemorrhage, SVM, NN**

I. INTRODUCTION

Intracranial hemorrhage is bleeding inside skull.It can be roughly classified into two types intra-axial and extra-axial. Intra-axial hemorrhage is spontaneous bleeding intothe brain tissue; it is also referred as cerebral hemorrhage or Hypertensive Bleed (HTN).Extra-axial hemorrhage can be further classified into Epidural hemorrhage (EDH),Subdural hemorrhage (SDH), and Subarachnoid hemorrhage (SAH). The objective of this paper is to detect EDH, SDH, and HTN.Nowadays X-ray, *Magnetic resonance imaging (*MRI), Computed Tomography(CT), and other medical imaging systems are commonly used and are important part of daily practice. Computed Tomography (CT) is used as one of the chief imaging techniques to help the doctors to diagnose the problem. Extensive way and rapid assessment of structural brain injuries .The mortality rate in the first 30 days after the hemorrhage is about 34.6%, which is the highest for any type of stroke [1]. However, according to medical specialists, early diagnosis of the condition and obtaining immediate and relevant treatment can be a lifesaver for affected patients. The main techniques and tools which help in diagnosis of hemorrhages is the human brain Computed Tomography (CT) image. An expert such as an experienced doctor can extract the important symptoms of hemorrhages from the image by naked eye. So idea behind paper is to develop an automated process which would do the basic diagnosis and detect the type of hemorrhage in order to help the doctor.

II. RELATED WORK

Important work in detection and diagnosis of hemorrhages require segmentation of image or hemorrhage area detection and decision making. Lot of research has been done in medical image segmentation and component detection. Spatial fuzzy c-meansclustering and active contours can be used for segmentation [2]. K means clustering can be used to detect suspicious hemorrhagic regions[3]. Another technique of extracting hemorrhages is by watershed algorithm, features of which are later provided to neural network [4].Wavelet based features of histogram can also be used as inputs to detection systems[5]. Selective median filtering is also used for segmentation of hemorrhagic part[6].

III. System Overview

Each CT image will undergo through following process(Fig.1) to annotate the presence and type of bleeding.

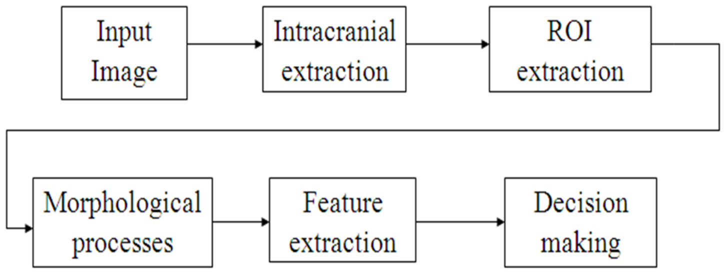


Fig 1. Block diagram of system overview

Our objective is to extract hemorrhages situated in intracranial area, so once intracranial area is extracted it will facilitate the extraction of ROI. Morphological operations are used to remove non-ROI regions and to create uniform and connected ROI. Different features like solidity, convex hull and contact area are extracted in order to ease decision making process.

A. Intracranial Extraction

The intracranial area is extracted by isolating the skull and scalp from the CT image of the brain. The skull always appears to be the largest connected component (Fig .2). In order to extract the intracranial area, we fill the region inside the skull. Then original CT image is subtracted from the obtained filled image. Finally we get the intracranial area by taking the negative of the obtained image(Fig .3).

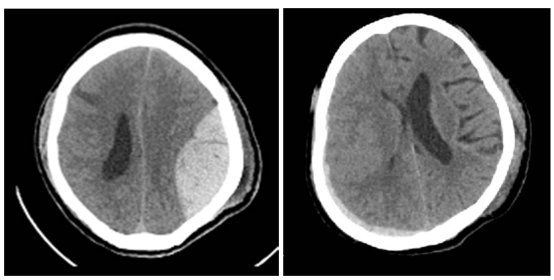


Fig. 2 Examples of CT image(EDH and SDH)

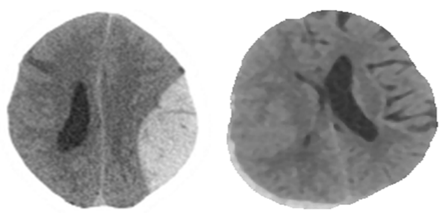


Fig. 3 Corresponding extracted intracranial areas

B. Image Enhancement & ROI Extraction

In order to ease the classification and detection process of the hemorrhage, we use some image enhancement tools. Median filter is used to reduce the salt and pepper noise from the image. In CT image, density values are represented as gray scale statistics, however not all possible density values can be displayed in discernible shades of gray. Thus density range of diagnostic relevance is assigned to the whole range of discernible gray values. "In the CT image of the brain, intensity values of blood lie within range of 160 to 220, which is detected by global thresholding.". We apply unique thresholding technique as the threshold for each image can differ. The histogram of brain CT image with hemorrhage is shown in Fig. 4.The hemorrhagic region is between 175 to 230 intensityscale while normal brain tissue is between 100 to 140 intensity scale.The value of histogram is nearly zero in between,that is the derivative of this curve crosses x axis as show in Fig. 5 which is our optimum threshold.

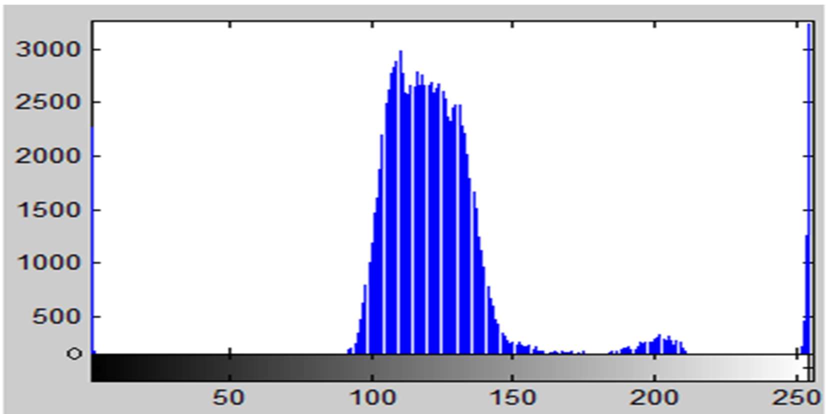


Fig. 4 Histogram of CT Image

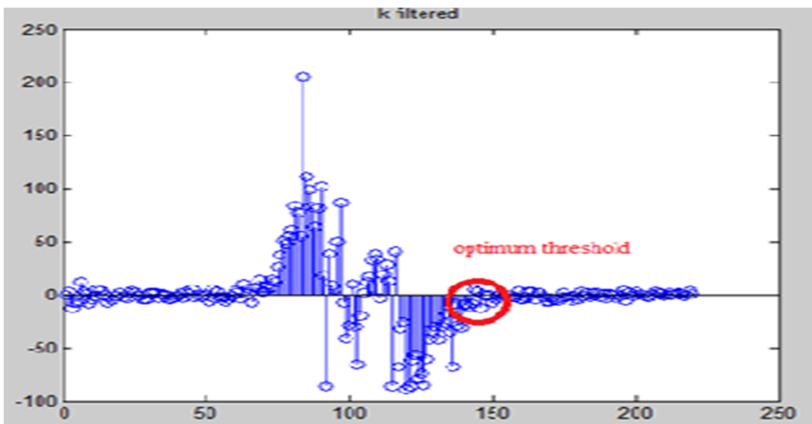


Fig. 5 Derivative of Histogram

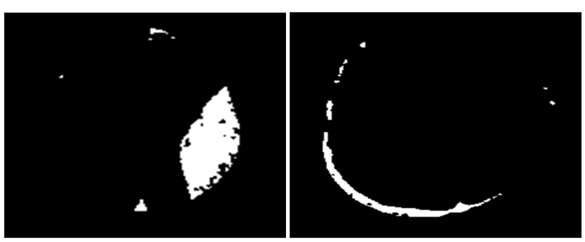


Fig. 6 Results of thresholding and image enhancement

Fig .6 shows the ROI extracted but with some noisy components.

C. Morphological Operations

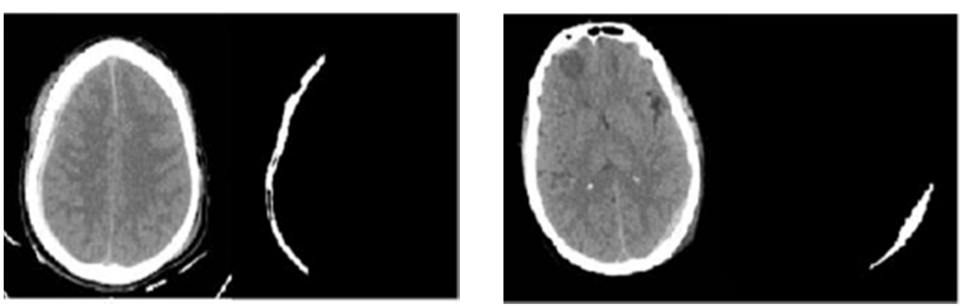
Global thresholding is likely to produce noisy result. The result also contains unconnected components. Morphology is a broad set of Image Processing operations that process images based on shapes. Image is transformed into binary image prior to morphological processing. The function of binarization here is to acquire all the connected components for normal and abnormal regions. Dilation and Hit and Miss Operations are used to eliminate unwanted components and get a uniform ROI[7].The image is dilated by kernel aligned to largest connected component in image which gives us uniform ROI while Hit and Miss Operations are used to eliminate noise(Fig. 7).

Fig. 7 Result of morphological processes

D. Feature Extraction

Geometric and textural features are extracted from ROI and original hemorrhagic bleed.Epidural hemorrhage (EDH) in most of cases is biconvex in shape while Subdural hemorrhage (SDH) in most cases is concavo-convex in shape, these peculiarities can be used to extract corresponding geometrical features. Convex images of SDH and EDH are shown in figure 8. Solidity and ratio of region area and major axis can successfully discriminate between SDH and EDH. Some examples of solidities are shown on Fig. 9, which shows that value for SDH is quiet low than of EDH .In SDH, blood gathers within the outermost meningeal layer, between Dura mater, which adheres to skull and arachnoid mater, which envelops the brain [8].While in EDH blood gathers between Dura mater and skull, so both have different kind of tissues around blood buildup, this property can be exploited by textural features. We compute Gray-Level Co-Occurrence Matrix (GLCM) of hemorrhagic part to get features such as contrast, correlation, energy and homogeneity. The features are extracted from every connected component. The features that are used for detection of hemorrhage are listed as in Table1 and Table 2. The extracted features are used as input to decision making model to discriminate between three types.

Fig. 8 Convex images of ROI



Solidity of hemorrhage is 0.24 Solidity of hemorrhage is 0.72

Fig. 9 Solidities of SDH and EDH

TABLE I GEOMETRIC FEATURES

Feature	Remark
Contact area	The number of pixels in contact with skull bone border
Region area	The number of pixels in the ROI obtained.
Solidity	The proportion of the pixels in the convex hull to original bleed region
Major Axis of Convex image	Major axis of Convex hull represented as image

TABLE II TEXTURAL FEATURES

Feature	Remark
Contrast	Measures the local variations in the gray-level co-occurrence matrix.
Correlation	Measures the joint probability occurrence of the specified pixel pairs.
Energy	Provides the sum of squared elements in the GLCM. Also known as uniformity or the angular second moment.
Homogeneity	Measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal.

E. Decision Making Process

In decision making the first criteria is applied to see whether the hemorrhage is present or not. This is done by applying threshold to the value of bleed area present. In order to classify HTN type of bleed, we apply another threshold for contact area between skull and bleed. Classification between EDH and SDH is then done using SVM and NN. Different features of bleed are given as input to both the classification methods.

Neural network: A neural network model is a powerful tool used for various real life applications like time series predication, sequence detection, data filtering, pattern recognition, and other intelligent tasks as performed by the human brain. There are various approaches defined under neural network for pattern recognition and depending upon the type of the learning mechanism applied to generate the output from the network, the appropriate approach is selected. The learning can be categorized as supervised learning in which the desired result is known to the system i.e. the system is trained with the priori information available to obtain the desired result. We have used back propagation algorithm for supervised learning using above features. The Multilayer Perceptron network based on supervised learning approach is trained using the back propagation algorithm. This network consists of three layers: input layer, output layer, and the intermediate layer i.e. the hidden layer. These layers consist of neurons which are connected to form the entire system. Weights are associated with the connections which marks the signal strength. The weight values are calculated according to the input pattern and the error function is back propagated to the input layer. The hidden layer updates the weight functions periodically under its value is minimized or reaches an acceptable[9].

Support Vector Machine (SVM): Support Vector Machine (SVM) is a one of the supervised learning methods for binary classification. The basic idea is to find a hyper plane which separates the d-dimensional data perfectly into its two classes. As the data is not linearly separable we have used kernels which cast the data into a higher dimensional space where the data is separable [10]. We used SVM in our final executable file as it requires less number of dataset for training purpose. Also for classification between two classes SVM yields higher accuracy. Hyper plane created by multi layered perceptron for classification may not be equidistant from both classes .In SVM, hyper plane is tried to adjust at center of classes with support of closest points to hyper plane .Thus classification error is less in SVM. Above features were given to SVM and Neural Networks to discriminate between EDH & SDH and results below were obtained. Figure 10 shows SVM plots for two features solidity and ratio of major axis to area

TABLE III. RESULTS OF CLASSIFIERS

CLASSIFIER	RECALL	PRECISION	ACCURACY
SVM(LINEAR)	0.875	0.913	0.88
SVM(QUAD & HIGHER DEGREE)	0.9583	1	0.97
NN(7 HIDDEN NEURONS)	0.83	0.87	0.852
NN(15 HIDDEN NEURONS	0.875	0.952	0.882

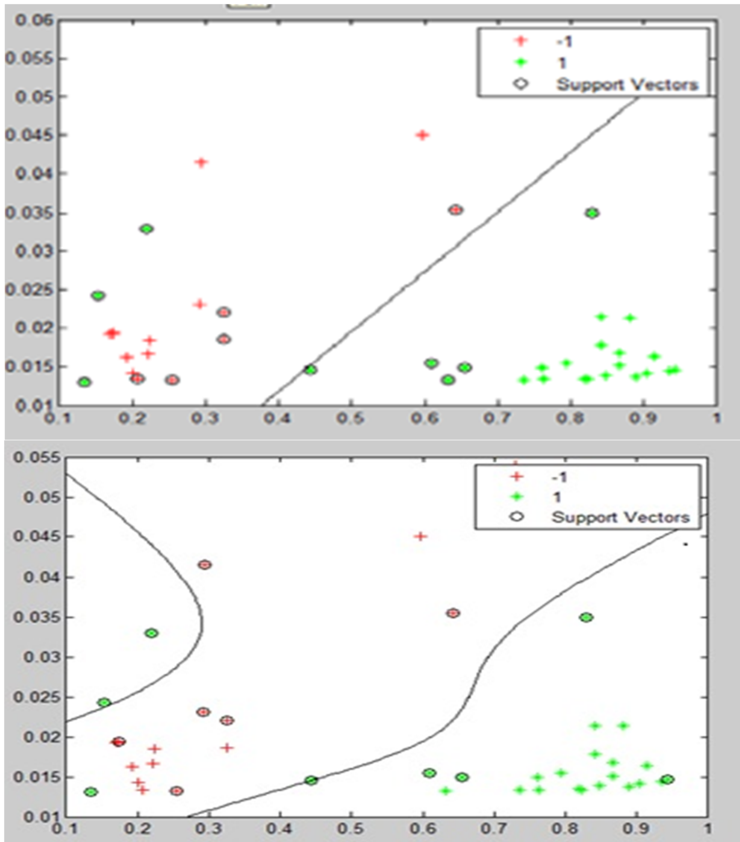


Fig. 10 SVM Plots (a. Linear kernel b. Quad. Kernel)

IV. RESULTS

After application of SVM and Neural Network ,we got results as shown in Table 3.

V. CONCLUSION

An approach for Brain hemorrhage detection and diagnosis is proposed in this paper. The encouraging results have been attained; we were able to achieve precision of one and recall of 0.9583 for database of 100 images. Plans for future work include detection of SAHand use of deformable templates to extract shape of hemorrhage. Plans also include creating large dataset for training neural network.

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