CAD SYSTEM FOR EARLY STROKE DETECTION AND CLASSIFICATION

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Abstract

Brain Stroke is a cardiovascular disease which happens when a block in the blood flow to the brain is blocked. For the Identification of brain strokes, the progress of the disease is to be monitored for the treatment of therapy. Computed tomography (CT) imaging is most extensively used in the analysis of stroke. Precise segmentation and classification of stroke exaggerated regions are necessary for correct detection and analysis. Image classification is a significant step for high level processing of self regulating of brain stroke analysis. Physical lesion demarcation is the standard approach at present, but it is mutually time-consuming and operator-dependent. To deal with these problems, we propose a method that can mechanically outline stroke present in CT images. The CAD system must meet the following requirements: identifying lesion area, detecting different types of stroke high accuracy rate, low lesion calculation time, high processing speed.

KeyWords: Preprocessing, Global Thresholding, GLCM, Feature Extraction, SVM Classifier.

1.Introduction

Brain Stroke is a chronic disease and third cause of death around the world. Brain Stroke happens when a part of brain is injured due to the deficiency of the blood flow as blood vessel bursts, spilling blood into the surrounding brain cells or is blocked by a clot, intervene the flow of essential oxygen and nutrients [1]. We can primarily categorize Strokes in two ways: 1) infarct stroke and 2) Hemorrhagic stroke. The ischemic stroke elucidates about 80 percent of all brain strokes. During healing, delineation between the two types in stroke is of primarily important [2].

Magnetic resonance imaging (MRI) and Computed tomography (CT) are mostly used methods for capturing brain images. CT imaging is favored due to wider accessibility, lower cost and susceptibility to early stoke. Mostly CT images provides information which are necessary to make decisions during crisis [3]. In CT images, a infract stroke affected region are viewed as a bright region while other region are contrasted in its surroundings. But he other turns out as a dark region while the contrast comparative to its surround confide in on the time taken since the stroke accrued. Sample images are shown in Fig. 1.(a) and 1.(b)

Fig 1.(a) Infarct Stroke(Black Area)

Fig 1.(b)Hemorrhage Stroke(White Area)

Computerized Tomography [CT] is been used to attain the CT images. This is based on a grouping of X-rays as they can be lapsed through the different parts of a patient’s body. An unreliable amount of X-rays are passed through the body confide in on the quantity that can be captivated from a particular tissue such as a muscle or brain [4]. The CT images are influencing workload for radiologists to examine the number of screening tests in a shorter time. These workloads can consequence in error in forecasting lesion area in the brain CT image. Therefore CAD systems are used to implement to aid the radiologists in lesion area detection and predicting the lesion size in an image.

Computer Aided System(CAD) can have the following goals.

- Improve accuracy in diagnosis;
- Early detection of stroke;
- Reduce the time of radiologists in report evaluation.

2. Literature Review:

Bala [5] proposed an improved Watershed Segmentation Technique based on edge detection algorithms and gradient operations. They have used noise removal techniques and the Image enhancement technique before applying Prewitt's edge detection technique to avoid over segmentation. This method shows accurate segmentation results and reduces the problem of over segmentation when compared with existing method.

MAHMOUD AL-AYYOUB et al. [6] proposed a fore mentioned approach based on the CT scan Images to find is there a brain hemorrhage available in the brain images. The system contains the following stages as most of the CAD Systems do have such as pre-processing of the CT image, Segmenting the image, feature extraction, and finally classification. The experimental results are in compressing levels with a recognition rate of 100% is achieved for predicting weather a hemorrhage is occurs or not. For the other type of stroke, more than 92% accuracy is accomplished.

Przelaskowski et al. [7] proposed a CAD system which uses wavelet based image processing technique to enhance the darker regions , which were often not very darker in CT scan review. The proposed CAD system was verified with various inputs. While analyzing the results it is found with increase in Sensitivity to 56.3% while compared with 12.5% of standard CT scan preview.

ALYAA HUSSEIN ALI et al. [8] proposed supervised classification process used to classify stroke area and its estimated stroke time. This method is used to color the image with jet colors for hemorrhagic and ischemic types to classify normal and abnormal parts depending on color feature. The process provides useful information that help to identify the stroke age and its transformation time that can assist to decide the best treatment or doing surgery to remove the stroke effects.

Mayank Chawla et al. [9] proposed a CAD system which also includes three stages: Detection of mid-line symmetry are done after image enhancement which is done in the level1 and the third stage will be classification of irregular slices. For improving the region of interest they have applied windowing operation. Demesne knowledge about the anatomical structure of the skull and the brain is used to notice anomaly in a rotation and translation invariant manner. They have applied a two level classification scheme to notice anomaly using features derived in the intensity and the wavelet domain. Finally the system have resulted with 90% accuracy and Predestining anomaly at patient level was found to be 100%; the system was capable of giving average precision of 91% and the rate of recall is observed at 90% in the slice level.

S. Mujumdar et al. [10] presented a CAD model for mechanically formative the window which improves the contrast of the image which resembles the ischemic lesions in the brain. The proposed CAD model executes a coarse segmentation of the lesions displaced by contrast-to-noise ratio based calculation of the optimal window parameters. The contrast enhancement of the lesions is approved by a region of interest study and by using the contrast improvement ratio metric.as a result the average obtained in enhancing the contrast varies from 25% to 60%. The effective approach applied in the segmentation results in reduction of the false positives and lesion boundaries were well enhanced.

3. Proposed Method:

The proposed CAD scheme operates on Digital Imaging and Communication in Medicine (DICOM) format obtained in CT imaging. The CT images which are used as input for CAD system are collected from the radiology department. The system requires a PC with MATLAB environment for execution.

Preprocessing:

Untimely recognition of stroke is very vital. The earlier stage of stroke could not be easily identified in the CT Images. But there are firm parts of a brain CT image which in reality constituents to radiologist when a person is diagnosing cerebrovascular accidents. Therefore enrichment of the images can make preferred features more observable. We brain CT input images are improved using a preprocessing technique. It happens because other parts available in the brain CT image such as bone tissues are not vital for analysis and unfavorably influence the decomposition coefficients [11]. Salt and pepper noise may be present in the captured CT image and hence median filter is applied. It is less sensitive when compared with linear techniques and it can eliminate salt and pepper noise without disturbing of the sharpness of an image. The original image and median filtered image are shown in Fig.1.

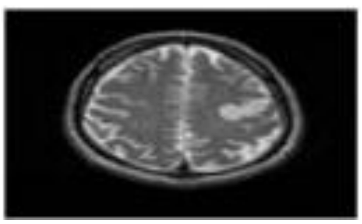

Figure 1.a Original Image

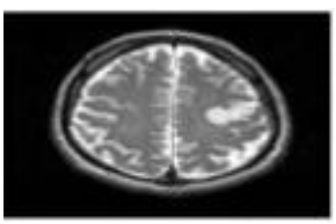

Figure 1.b Median Filter Image

B. Segmentation

The segmentation process is used to detect lesions present in the CT image. There are numerous segmentation methods are available but thresholding is one of the most well-liked techniques in which all pixels having intensity values above or below some level are categorized as part of the segment. In thresholding, the input image is converted from an intensity image to a binary image. For the boundry selection of the histogram image a global threshould algorithm is applied. An image is alienated into blocks of fixed size, and the pixel variation of every block is used for decree the boundary blocks that a bimodal histogram. For categorizing the object blocks and background blocks Otsus Thresould is used. The average values were used to obtain the optimal threshould value. The results proves us the projected algorithm shows a better output than the conventional thresholding menthods for different images captured from CT [12].

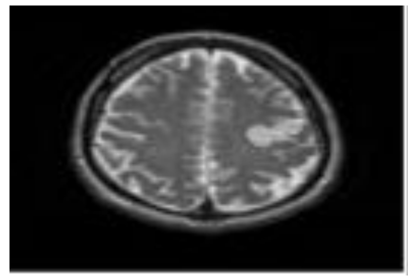

Figure 2.a Original Image.

Figure 2.b Otsu Threshold Image

C. Feature Extraction

The feature extraction is the process to decrease the false positives by calculating certain features that distinguish one sample from the other. It is a difficult chore to dig out good feature set for classification. There are quite a few texture based feature extraction methods are available but Gray Level Co-occurrence Matrix (GLCM) is very general. The statistical features are obtained based on smoothness and the texture connected knowledge of the image. The normalized feature vectors are estimated for each pixel in the generated data. The following features are obtained using the GLCM method.

- The spherical disproportion of the system determines the promptness of the margins of an entity and is calculated using the formula:

$$D=\frac{A}{4\pi R\hat{}2}$$

$$R=\sqrt[3]{\frac{3w}{4\pi}}$$

Here R symbolizes the radius of the sphere with volume w and A is the area of the entity.

- The spherical density of the system calculates the dense an object using the formula:

$$E = \frac{100a}{n}$$

Here a is the number of voxels values and n is the volume of the object.

- The pondered radial distance calculates the smoothness degree of an object using the formula:

$$\text{Drp}=R^{-1\sum_{i,j,k} C_{i,j,k}}$$

$$C_{i,j,k=\frac{3}{4\pi}}\left[\left(r_{i,j,k}+0.5\right)^3-\left(r_{i,j,k}-0.5\right)^3\right]^{-0.1}$$

Here R is the estimated radius, $C_{i,j,k}$ represents the pondering coefficients applied to each voxels and $r_{i,j,k}$ represents the radial distance of the voxels.

- The Sphericity calculates how much the contour of an object proximate of a spherical shape using the formula:

$$Es=\left(6A^{\left(\frac{2}{3}\right)}\pi^3\right)X^{-1}$$

Here A is the volume of an object and X is the area of an object.

- The Elongation calculates the expansion of an object using the formula:

$$\text{EI}=\frac{Ar_{min}}{Ar_{max}}$$

Here Ar_{min} represents the dimension of the less important corner of the minimal box and Ar_{max} represents the dimension of the superior corner of the minimal box.

- The Boyce-Clark radial shape index calculates the promptness of the shape of an object using the formula:

$$Bc=\sum_{i=1}^{n}\left|\left(\frac{100r_i}{\sum_{k=1}^{n} r_k}\right)-\frac{100}{n}\right|$$

Here n is the number of voxels in the limits of the volume. r_i and r_k are the distance of explicit border voxels to the middle of the object.

The texture features are intended based on the co-occurance matrix of the volume using the formula:

$$Co(j,k)=\left|quant\left(A_{x,y,z},v\left(A_{x,y,z,}\alpha\right)\right)\right|A_{x,y,z}$$

$$=\text{i,x}(A_{x,y,z},\alpha)=j,\alpha\epsilon\{1,\ldots,26\}$$

Here x is the function which gives one of the 26 tri-dimensional neighbors of a voxel. $A_{x,y,z}$ is the evaluation of the voxel. The texture feature extraction methods are calculated below:

- The energy (E) is defined as the assess of the area of pixel pair recurrence. It measures the consistency of an image using the formula:

$$\text{E}=\sum_{i=0}^{G-1}\sum_{j=0}^{G-1} Co(i,j)^2$$

- The entropy (Ent) is used to typify the reliability of an input image. Its value will be greatest when all the elements of the co-occurance matrix are identical. Then entropy can be calculated using the formula:

$$\text{Ent}=\sum_{i=0}^{G-1}\sum_{j=0}^{G-1} -Co(i,j)\log(Co(i,j))$$

- The contrast (Con) is defined as a determine of intensity of a pixel and its adjacent over the image. It is gritty by the dissimilarity in the colour and brightness of the object and the other object within the corresponding field of view.

$$\text{Con}=\sum_{i=0}^{G-1}\sum_{j=0}^{G-1} Co(i,j)(i-j)^2$$

- The Inverse Direct Moment(IDM) is also called as Homogeneity that calculates the local homogeneity of an image. It has an array of values so as to resolve whether the image is textured or not. It is calculated using the formula:

$$IDM=\sum_{i=0}^{G-1}\sum_{j=0}^{G-1}\frac{1}{1+(i-j)^2}Co(i,j)$$

- The Directional Moment (DM) is computed by considering the alignment of an image as a measure in terms of an angle and is defined using the formula:

$$DM=\sum_{i=0}^{G-1}\sum_{j=0}^{G-1}\frac{(Co(i,j))^2}{1+|i-j|}$$

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The contrast of an image is 0.073805
The correlation of an image is 0.983944
The cluster prominence of an image is 100.752098
The cluster shade of an image is 5.953670
The dissimilarity of an image is 0.063748
The energy of an image is 0.397232
The entropy of an image is 1.240963
The homogeneity of an image is 0.969783
The maximum probability of an image is 0.492184
The sum of squares:variance of an image is 8.145747
The auto correlation of an image is 8.184873
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Fig 3. GLCM feature values of the given input image.

D. Classification

Classification is constituted with a CAD system where classifier select an unknown sample to a predefined class based on preceding knowledge. SVM carry out pattern classification by formative unraveling hyperplane with utmost reserve to the closest points in the training set [13]. These points are called support vectors. The process is explained in figure 4. The decision function of SVM is

$$f(x)=sign\left[\sum_{i=1}^{N}\alpha_i y_i K(x,x_i)+b\right]$$

Where the data point to be categorized represented as x , xi will be support vector, quantity of support vectors represented as N, constant determined (b) from training and yi ∈ {−1, 1} will be the the class label of the support vector xi . The coefficients αi are the solutions of a quadratic programming problem. The margin is the distance of the support vectors to the hyperplane, is

$$M=\frac{1}{\sqrt{\sum_i^N \alpha_i}}$$

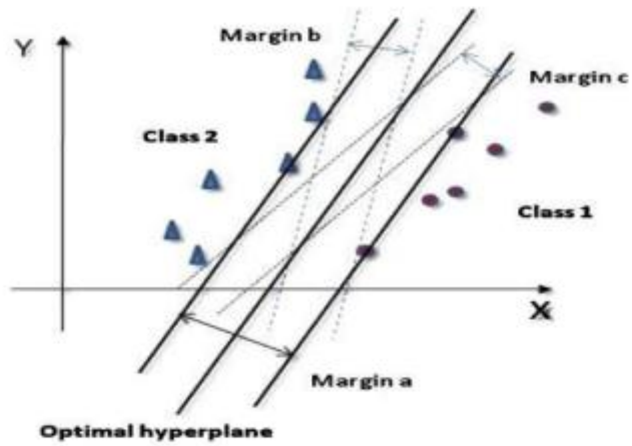

Figure 4. SVM Classifier

4. Experimental Results:

In the proposed system, median filter is used to eliminate noise from the original image and to get better the accuracy of the outcome. The MATLAB coding for median filter is medfilt2. The global image threshold technique is used in segmentation of brain stroke and the code is graythresh command to perform segmentation task. GLCM feature extraction technique is used to extract the features of the processed image. The GLCM feature extraction method is resolved using graycomatrix in MATLAB. For Classification SVM technique is used. The performance of the proposed system can be calculated based on true positives and false positives. The CAD System is evaluated using LIDC database and the lung nodules present in the image is annotated by radiologists.

1. Sensitivity:

$$Sensitivity=\frac{True\ Positive}{True\ Positive+False\ Negative}$$

Here True Positive means slice segmented containing brain lesions nodules False Negative means slice segmented containing brain lesion is precisely classified as non-brain stroke lesion.

2. **Specificity:**

$$\text{Specificity}=\frac{True\ Negative}{True\ Negative+False\ Positive}$$

Here True Negative means slice segmented without brain lesions nodule is precisely classified as non brain lesions. False Positive means slice segmented without brain lesions nodule is precisely classified as brain lesions.

3. **Accuracy:**

$$\text{Accuracy}=\frac{TP+TN}{TP+TN+FP+FN}$$

Here True Positive means sliced segmented containing brain lesions nodules.

True Negative means slice segmented without brain lesions nodule is classified as non-brain lesions.

False Positive means slice segmented without brain lesions nodule is classified as brain lesions.

False Negative means slice segmented containing brain lesions nodule is classified as non brain lesions.

In this proposed method, there are two categories of training images are used. They are brain stroke image and non-brain stroke image. Entirely we use 200 images to train the classifier. Of these 100 images are brain stroke image and 100 images are non- brain stroke image. The accuracy of the system is 93% and the sensitivity of the system is 95% and the specificity of the system is 92.5%.

5. Conclusion:

In this paper we proposed a CAD system to identify the brain stroke nodules present in DICOM images. The proposed system uses otsu threshold method to segment the image and GLCM method is used for feature extraction technique. The SVM classifier is used to categorize the images. The projected system can be used to sense the brain stroke at early stages and augment the patient's endurance. The projected method helps the radiologists in identifying brain stroke and take correct actions. The projected system has fewer positive values and the performance of the system is considered using the statistical parameters. The system has 93% accuracy, 95% sensitivity and 92.5% specificity.

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