SLIC Segmentation for Tumor Detection & Classification using SVM

Pooja Shah, Rajkumar S

Abstract*: *Uncontrolled growth of cells in brain is termed as brain tumor. Tumor almost gets double within 25 days. If it is not detected at early stage, it may lead to death nearly in six months. Human inspection through MRI or CT scan images are time consuming. Scanning large number of images by human is time taking and result may not always be correct. For this reason, an automated tumor detection process is required which helps scanning image faster and model which give correct results always. Our proposed system aims for differentiate between the MRI images with non-tumor or tumor. By using the super pixel segmentation, it will detect the tumor region and further with the SVM classifier it will classify the type or tumor (e.g.: pituitary tumor, meningioma or glioma). Proposed model identifies tumor more accurately with the accuracy of 87% compared to current traditional method.

Index Terms*: *Support Vector Machine, Super pixels, Median Filtering, SLIC

I. INTRODUCTION

Uncontrolled growth of cells in body is termed as tumor whereas uncontrolled growth of cell in brain is termed as brain tumor. Tumor cells that are non-cancerous and uniform in structure also which will not spread are termed as benign whereas malignant tumor cells are non-uniform in structure, are cancerous and have active cells which spread to other organ and the tissues. Pituitary tumor is high grade tumor classified as malignant whereas glioma and meningioma are low grade tumor classified as benign. Benign tumor is curable with the surgical operation. Malignant tumor needs radiotherapy or chemotherapy. There are various methods available for brain tumor detection. From that segmentation is the most important one. Segmentation divides the target image into number of smaller images based on intensity, contrast or color. MRI Images are used for the detection purpose compared to CT scan because they are more effective as they do not use radiation. Proposed system performs automatic brain tumor classification and detection. It is divided into 3 steps:

- Preprocessing
- Feature Extraction
- Feature Classification

In first preprocessing step, median filtering is applied which removes salt and pepper attack from images. After that skull are removed from the MRI image to process the image faster. Features like contrast, intensity, dissimilarity, etc. are calculated to generate feature vector space for image classification. Further classification algorithm SVM, which classifies images into three sub classes. Various tests are performed on number of MRI images and appropriate features are selected to achieve better performance.

II. LITERATURE SURVEY

Xiao & Kai [1] proposed system to find features which shows relation between deformation in brain and tumor region. It is divided into 4 different steps: Preprocessing, next is feature selection, followed by segmentation and classification. Unnecessary data are removed from background in first step. Feature extraction is done using lateral ventricular. For classification methods like C-mean and KNN are used. Limitation of this system is once mask is placed undesired pixel get removed which leaves extracted brain region, which may sometime remove tumor region as well.Nandagopal and Rajamony [2] considered the combination of texture and statistical features using WCT & WST, using wavelet transformation tumor were classified into two groups: benign and malignant. It is also divided into four steps:Preprocessing, next is feature selection, followed by segmentation and classification.SVM used for classification is combined with WCT &WST is used for feature extraction and selection. Similarly, PNN used for classification with WCT & WST for feature extraction. PNN classifies brain tissues. Limitation of this system is it works only with CT images.Method to classify MRI images to normal and abnormal is proposed by Kalbhani [3]. Here first 2d DWT of input image is obtained. After feature vector normalization, PCA is used to extract redundancy from primary feature vector. Finally, KNN is applied to determine the type of image. Limitation they cannot be applied on asymmetric images.Sindhu mol [4] came up with angular feature extraction and clustering component for brain tumor classification. It is divided into two steps:First one is segmentation and second is analysis. Initially, clusters are created using MRI images and component are analyzed using SVM. Main limitation of this system is that when threshold value goes down it leads to large number of computations for feature extraction.Dimensional reduction-based feature extraction was proposed by Navarro [5]. Classification is achieved using hoc and echo times which are short. Here in this model, feature selection is an independent task. Model prepared based on bootstrap samples which uses iterative procedure. There are large resource consumption and time complexity is large for this system causes for demerit.Paper by Saritha [6] talks about probabilistic neural network algorithm. It is divided into two steps: entropy-based feature extraction by using spider web plot graph and classification using PNN.

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It works on MRI images. Accuracy achieved in this system is 72% which is comparatively low.
Entropy value is a single sol dated feature helpful for MRI image, but result was less accurate compared to other existing technologies.
Neural Network techno tip was used by Sumitra and Saxena [7]. They divided steps as follows: feature extraction, with dimensionality reduction and classification using BPN classifier. GLCM features like correlation, intensity min as well as max, median and variance are extracted for each MRI images. Back propagation the major concept in neural network is used for classification. Tumors are classified into two classes malignant and benign. Accuracy achieved using BPN classifier is only 73% but it is fastest.
Performance issues was the major concern for this system.

III. PROPOSED SYSTEM

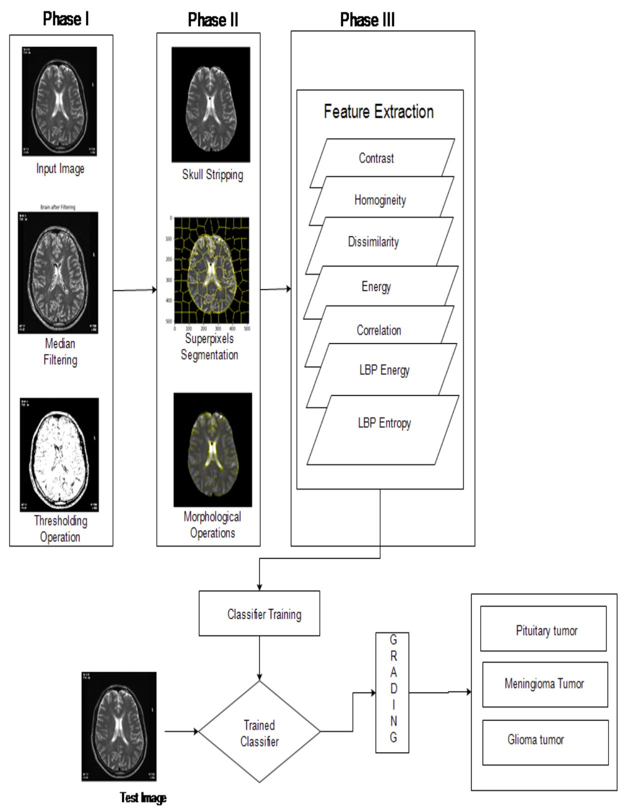

Fig. 1. Proposed System Architecture

A. *Pre-Processing*

Pre-Processing improves the quality of the MR Images so that it can be processed in a better way. It removes the noise from image to improve parameters like signal to noise ratio and undesired part from the background, enhancing the visual appearance of the image by preserving its edges. Here we will use median filtering.

B. *Median Filtering*

Median filtering is non-linear and removes 'salt and pepper' attack from the images by preserving the edge and it is non-linear as well. Median filtering runs on the images pixel and replaces individual value by the median value of neighbor pixel. Median filtering selects the window size which slides pixel by pixel. Initially, pixels in window are sorted and the middle value is replaced by median value.

C. *Thresholding Operation*

Thresholding operation basically converts gray scale image into binary image. Levels are decided and assigned to given images based on the threshold value. As it is binary Thresholding, where gray scale image pixel will range from 0 to 255, 0 is assigned to 0-127 and 1 is assigned to pixel above 127. Thresholding of image is calculated by Eq. (C.1)

$$G(x,y) = \begin{matrix} 1, if(x,y) > T \\ 0, if(x,y) < T \end{matrix} \quad (1)$$

Here, *f (x, y)* indicates individual pixels in the input image and *G (x, y)* indicates individual pixels in the output image.

D. *Skull Stripping*

It is a process of removing the outer area of brain or say non-brain tissues from brain. Skull stripping is done so that image can be analyzed in more effective way. Skull stripping can also remove tissues like fat, skull or non-cerebral tissue from the brain images. Technique available for skull stripping are 1) Histogram based skull stripping 2) Skull stripping based on image contour or 3) Threshold Value based skull stripping. Here we will use threshold-based skull stripping to remove skull tissues.

E. *SLIC super pixels Segmentation*

SLIC is used to perform local clustering of images. It uses 5D space [Lab]. CIELAB as color space and x, y coordinate pixels. Compactness and regular super pixel shapes are achieved by using various distance measurements.

Here clustering is done by color likeliness and closeness in image plane. CIELAB is used for small color distance otherwise for large distance 5D space [*labxy*] is used.
Distance measurement formula can be given as below:

$$\begin{gathered} d_{lab} = \sqrt{(l_k - l_i)^2 + (a_k - a_i)^2 + (b_k - b_i)^2} \\ d_{xy} = \sqrt{(x_k - x_i)^2 + (y_k - y_i)^2} \\ D_s = d_{lab} + (m/S) * d_y \end{gathered} \quad (2)$$

F. *Morphological Operation*

Operations that extract boundary area from MRI image are called as morphological operation. There are two types of morphological operation 1) Dilation – Operation that add pixels to boundary area of objects whereas 2) Erosion – Operation that removes the pixels from the boundary region of the objects. Here we are using dilation followed by erosion because it removes the small holes from foreground objects or black dots in objects.

G. *Feature Extraction*

Process of collecting information from an image like intensity, contrast, etc. is called as feature extraction.

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This information is high level information that is collected in order to reduce computation on large set of images. This information is further used for machine learning purpose for increasing the accuracy in the system. By selecting proper set of feature the proposed system efficiency and accuracy can be effectively increased. Here we will extract various texture features.

1) GLCM (Gray Level Co-occurrence Matrix)

Indicates the probability of two gray points at distance direction.
Extracting texture feature involves two steps. Initially, GLCM is computed from an image and then textual features like contrast, dissimilarity, homogeneity, energy and correlation.

Contrast (C_{on}): Intensity of neighbor pixel and current reference pixel is measured.

$$C_{on} = \sum i \sum j \; |i-j|^2 \, p(i,j) \quad (3)$$

Dissimilarity (Dis): It is the distance between region of interest and pairs of pixels.

$$Dis = \sum i \sum j \; |i-j| \, p(i,j) \quad (4)$$

Homogeneity (H): It describes closeness between elements of 8ujGLCM diagonal and GLCM elements.

$$H = \sum i \sum j \frac{1}{1+|i-j|^2} p(i,j) \quad (5)$$

Energy (E): Angular momentum measured using homogeneity.

$$E = \sum i,j \; p(i,j)^2 \quad (6)$$

Correlation (C): Describes how current reference pixel is related to neighbor pixels.

$$C = \sum i \sum j \frac{(i-\mu_i)(j-\mu_j)p(i,j)}{\sigma_i \sigma_j} \quad (7)$$

2) LBP (Local Binary Pattern)

It describes the local structure of images. It calculates the LBP operator by comparing each pixel of image with the pixel around it (8 - neighbor). If pixel around is greater than current pixel it is marked as 1 else 0.

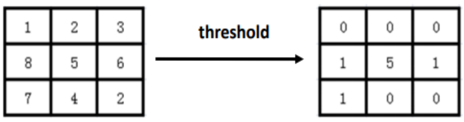

Fig. 2. LBP Operator

3) Hu Moment

Hu Moment is set of seven features which are transformation invariant and are calculated from central moment. First six moment are proved to be invariant of transformation, rotation, scaling and reflection whereas 7 moment changes on image reflection.

$H_0 = \eta_{20} + \eta_{02}$

$h_1 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2$

$h_2 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2$

$h_3 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2$

$h_4 = (\eta_{30} - 3\eta_{12}) + (\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + (3\eta_{21} - \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]$

$h_5 = (\eta_{20} - \eta_{02})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2 + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03})]$

$h_6 = (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + (\eta_{30} - 3\eta_{12})(\eta_{21} + \eta_{03})[(3\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]$

(8)

H. *Support Vector Machine (SVM)*

SVM is generally a binary classifier or supervised learning classifier algorithm. It comes under the category of machine learning algorithm. It partitions the feature vector into two sub spaces. It is also further modifying to classify into more than two classes for real world problems. It runs basically on training data set. Error caused by the trained algorithm on test data is not utilized during training. When data outside the train dataset is applied to SVM, it performs well. Training samples which are difficult to classify are called as support vectors. Formulation of SVM is changed by least square value in function. This reduces the computation and complexity for classification of problem. SVM is divided into two stages. First stage is the training stage where SVM learns itself by providing training dataset to learning algorithm. During this phase SVM select suitable boundary for the classes. And other stage is the testing stage. Here MRI images are classified into three separate classes such as pituitary, glioma and meningioma.
Main advantage of SVM classifier is that it works well in high dimensional feature space. Also, it gives more accurate results.

IV. EXPERIMENTAL RESULTS

To demonstrate the performance of proposed brain tumor detection, scheme several performance measures like accuracy, specificity and sensitivity are used. Here we are using brain tumor dataset containing 500 x 500 MRI images from 233 patients, 3064 T1-weighted enhanced.

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These images contain 3 kinds of tumor: meningioma (708 images), pituitary tumor (930 images) and glioma (1426 images).[12]
Input Image and finally extracted tumor are shown in Fig 3 and Fig 8 respectively.

A. *Phase – I*

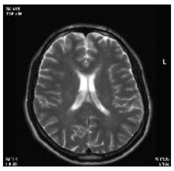

Fig. 3. Input Image

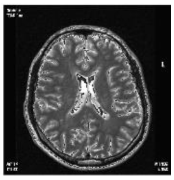

Fig. 4. Median Filtering

Fig. 5. Thresholding

B. *Phase – II*

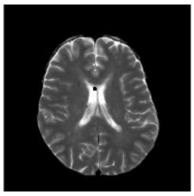

Fig. 6. Skull Stripping

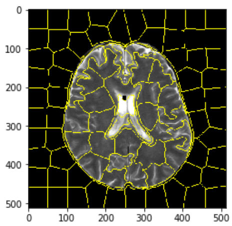

Fig. 7. SLIC Segmentation

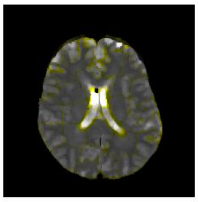

Fig. 8. Morphological Operation

C. *Phase – III*

TABLE 1. GLCM & LBP Texture Features

Images	Contrast	Homogeneity	Dissimilarity	Energy	Correlation
Image1	573.2834	0.3570	8.4708	0.8900	0.1680
Image2	567.8678	0.3232	9.5590	0.8916	0.1650
Image3	543.3604	0.3410	8.6296	0.8757	0.1664
Image4	549.7157	0.3445	8.6208	0.8827	0.1667
Image5	554.4967	0.3474	8.5535	0.8735	0.1669

TABLE 2. LBP Features

Images	LBP energy	LBP Entropy
Image1	0.1913	2.6821
Image2	0.1867	2.6939
Image3	0.1885	2.6942
Image4	0.1883	2.6950
Image5	0.1890	2.6932

TABLE 3. Hu Moment 1-3(a) and 4-7(b) features

Images	Hu Moment (1)	Hu Moment (2)	Hu Moment (3)
Image1	2.13222821e-03	9.94452979e-08	5.63667333e-11
Image2	1.49884406e-04	8.67553563e-10	4.07778393e-15
Image3	1.80194746e-04	1.27894525e-10	8.94413626e-15
Image4	2.47563873e-04	9.71304406e-10	1.13483457e-13
Image5	1.54117610e-04	7.32114570e-10	3.10008057e-15

(a)

Hu Moment (4)	Hu Moment (5)	Hu Moment (6)	Hu Moment (7)
2.29945954e-11	7.24410225e-22	6.97389084e-15	4.00700042e-22
1.79807641e-15	4.57403907e-30	5.14521358e-20-	1.66842450e-30
6.94704622e-16	1.73165429e-30	7.56409021e-21	1.07010139e-32
7.93808139e-14	7.05464776e-27	2.27346409e-18-	2.64513826e-27
5.68522263e-15	2.24692879e-29	2.24692879e-29	1.53286312e-19-

(b)

V. PERFORMANCE MEASURES

A. *Confusion Matrix*

Matrix generated based on the predicted values by the given model. Shows the classification details based on actual values and the predicted values in terms of true positive and true negative terms.
Accuracy - Accuracy is the ratio of no of positive detection by the total no of test
Sensitivity - Give the total positive fraction that is correctly detected.
Specificity - Give the total negative fraction that is correctly detected.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} * 100$$

$$\text{Sensitivity} = \frac{TP}{TP+FN}$$

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (9)$$

TABLE 4. Feature Selected and obtained accuracy

Feature Selection	Accuracy (%)
GLCM [7]	71.01
LBP	52.09
Hu Moment	75.02
GLCM [7] & LBP	80.53
GLCM [7] & Hu Moment	87.06
LBP & Hu Moment	79.96
GLCM [7] & Hu Moment & LBP	85.06

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TABLE 5. Accuracy Comparison with existing system

System	Accuracy
Proposed	87.06 %
Sumitra & Saxena [7]	73%

VI. CONCLUSION

Different features where selected and analysis was performed to obtain more accuracy. From Table 4 we can conclude that GLCM & Hu Moment features gives the more accuracy 87.06 percent compared to another feature selection. Also, from Table 5 as compared to current system where BPN classifier was used for classification and obtained accuracy is 73%, our system with SVM classifier gives more accuracy of 87.06 %.

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