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A New and Robust Segmentation Technique Based on Pixel Gradient and Nearest Neighbors for Efficient Classification of MRI Images

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***Abstract*— This paper proposes a new fully automated method for the segmentation of tumour in a tumour affected brain MRI image and its classification from a normal image. The technique detects brain tumour on the basis of differences in pixel intensities between the tumour and the surrounding tissues. It also exploits the connected pixels labelling of the tumour pixels which accurately segments brain tumour. Classification is done using support vector machine (SVM) which uses GLCM technique to calculate feature vector. The classification parameters (i.e. accuracy, sensitivity and specificity) and other parameters (i.e. speed and computational power used) show that our method is better in performance as compared to the other state of the art methods.**

Keywords—GLCM, MRI, SVM, Solidity and Thresholding.

I. INTRODUCTION

Brain tumour [1] [11] is one of the major causes of death among men throughout the world. It is the growth of some abnormal tissues within the brain. It's mainly of two types: one is benign tumour and other is malignant tumour. Malignant tumour is more dangerous than benign tumour as it is cancerous in nature and has the ability to grow inside the brain, thus malignant tumour can result in death if not diagnosed at an early stage. MRI is one of the techniques of medical imaging which helps in detecting tumour accurately. Radiologists can easily examine a brain MRI image to conclude whether it is normal or cancerous. But the problem arises when there are numerous images to be examined leading to decreased accuracy and high time consumption. Hence, in order to increase the accuracy and minimize the time consumption, automated classification with the help of computer technology is needed.

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The methodology includes the following steps: Image pre-processing, segmentation, feature extraction, and classification. Image pre processing is used to remove noise from an image to make it suitable for further processes. It is needed for the accurate segmentation of tumour from the image. Segmentation refers to the process where only the desired part of the image is kept and the unwanted parts removed. It is required to extract the region of tumour in the image making the classification easier and accurate.

Feature extraction is the processing of some calculated parameters from the segmented images which acts as input to the classifier for classification. It further reduces the information in image to a minimum level. For accurate classification, features which are extracted should be meaningful and useful.

Classification process differentiates a normal image from an image having a tumour with the help of algorithms known as classifiers. There are many types of classifiers which can be used for such purposes. Some of them are support vector machine (SVM) [2], k nearest neighbours (KNN) [3], Artificial neural network (ANN) [4], Probabilistic neural network (PNN) [5] etc. Each of the classifier has its own advantages and disadvantages. K-NN [3] has some limitations such as high computation cost, difficulty in finding the proper value of 'K' parameter etc. Even though K-NN [3] has high accuracy in classification, its performance is degraded by its limitations. PNN [5] has a major problem that it is a very slow classifier. ANN [4] performs better than the above mentioned classifiers with the high dimension of feature vector, but it also has high computational cost problem. As feature vector is small in our method, SVM [2] performs the best amongst all the other classifiers.

Classification is divided into two parts: training and testing. In training, known data is given to the classifier for its training. After that unknown images are given to the classifier for classification for testing. The efficiency of classification mainly depends upon the training.

This Paper is organized as follows. Section II describes the methodology utilized for the proposed method .Section III describes experimental work of the proposed method. The tumour classification and experimental results are given in section IV with conclusion in section V.

II. METHODOLOGY

The methodology used for the classification of brain MRI image of a normal person and a person having brain tumour is shown in fig.1. This system consists of the following modules: pre-processing (RGB to grayscale conversion, resizing and filtering), segmentation, feature extraction, training and testing. Firstly, training dataset of brain MRI images is given to the system for training of classifier. Then testing data set is given to the system which classifies it into two categories normal and abnormal based on the training.

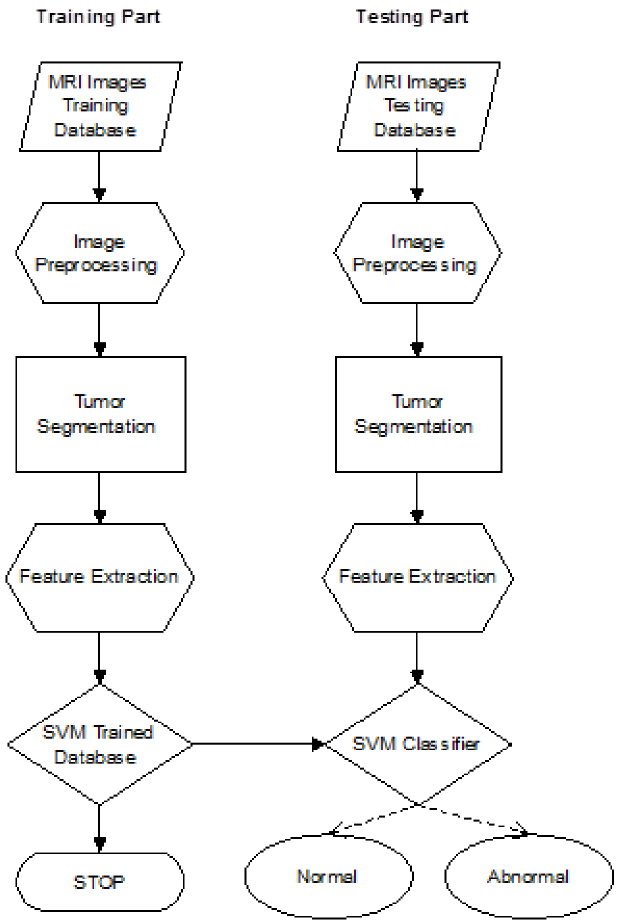
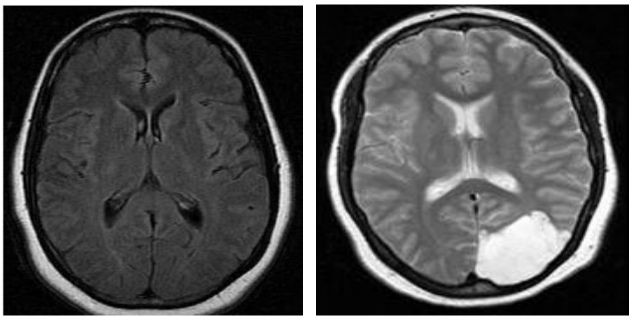


Fig.1. Block Diagram

A. MRI Image

The MRI (magnetic resonance imaging) [6] is one of the best tools used in hospitals and clinics for medical diagnosis of various diseases. Some of its advantages are: (i) It prevents exposure of body from ionizing radiations. (ii) It gives very high contrast between the tissues.

Fig 2 shows the MRI image of normal and abnormal brain respectively. It is clearly seen that the tissues affected from tumour are of higher intensity than the normal tissues. When the image is taken, it is an RGB image. Before giving it to the system, image is first converted to gray scale and resized to a size of 500 X 500.



(a) (b)

Fig.2. Brain MRI (a) Normal and (b) Abnormal

B. Pre-processing of image

Pre-processing includes filtering of image using median filter. At the time of acquisition, the image gets distorted with noise and the contrast is also low which leads to lower efficiency in further steps of the process. Filtering is needed to remove noise and to enhance image contrast. Advantage of using median filter is that it removes the noise while preserving the edges which helps in improving contrast of the image. Accuracy of tumour segmentation is also increased by this step. Filtered image is shown in fig 3.

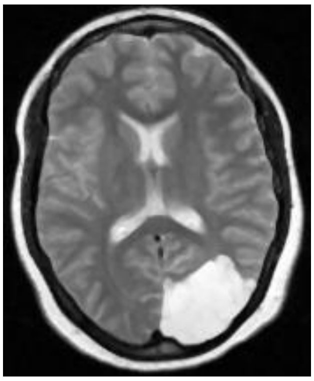
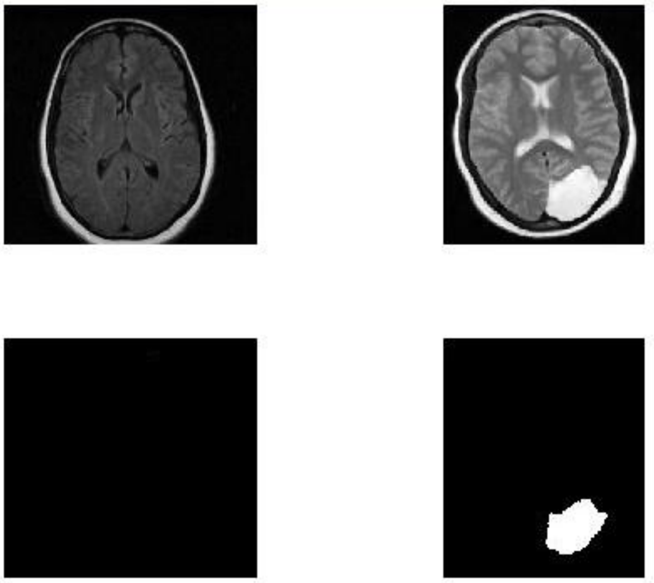


Fig.3. Filtered image

C. Segmentation

In the field of biomedical imaging, tumour detection is a crucial task as brain tumour can be a severe disease if not properly diagnosed. In the acquired MRI image, it can be seen that generally the intensity values where tumour is present is greater in comparison to the surrounding intensities. In our work, segmentation is done using intensity values and solidity of the tumour to detect the tumour from its surrounding tissues. The first step in segmentation is thresholding, where the intensity values greater than predefined thresholds are kept and the values below the threshold level are ignored. The threshold level is found by hit and trial method. We get a value of 164 as our threshold. After thresholding, the image still contains unwanted regions along with the tumour region. For removing these unwanted regions, solidity and area [7] of the segmented regions are calculated. Only those regions having solidity values greater than 0.2 are labelled as tumour intensity values. The second criteria is area where the max area of the region is considered as tumour based region. After exploiting these properties, the MRI image is segmented to detect the tumour as foreground and surrounding tissues as background.



(a) (b)

Fig.4. (a) Normal Brain MRI with its segmented image and (b) Abnormal Brain MRI with its segmented image

The segmented results are shown in fig.4 in which the two images are segmented where first image contains a tumour and second image is a normal MRI image. The segmented results are also shown as there counterpart images.

D. Feature extraction

Feature extraction plays a very important role in image processing /computer vision for pattern recognition and classification. A raw segmented image cannot be given directly to the classifier as it contains unwanted data which increases computational time and cost of the process. Some meaningful and important data points are extracted from the image (also called features) using feature extraction process. Features can be of many types such as intensity based features [12], texture based features [13] or shape based features [14]. Several features are calculated from an image which forms a feature vector which is given as input to a classifier for accurate classification of normal and abnormal MRI image. In our work, we are calculating 5 texture features using Grey Level co-occurrence matrix (GLCM) [8] technique which constitutes a feature vector of 5X1 dimension for each image. Features using GLCM are given by:

CONTRAST: Contrast is defined as the separation between the darkest and brightest area.

$$Contrast = \sum_{i,j=0}^{n-1} P_{ij}(i-j)^2 \tag{1}$$

CORRELATION: Correlation is computed into what is known as the correlation coefficient, which ranges between -1 and +1.

$$Correlation = \sum_{i,j=0}^{n-1} P_{ij} \frac{(i-\mu)(j-\mu)}{\sigma^2} \tag{2}$$

HOMOGENEITY: Homogeneity is defined as the quality or state of being homogeneous.

$$Homogeneity = \sum_{i,j=0}^{n-1} \frac{P_{ij}}{1+(i-j)^2} \tag{3}$$

ENTROPY: Entropy is a measure of the uncertainty in a random variable.

$$Entropy = \sum_{i,j=0}^{n-1} -\ln(P_{ij})P_{ij} \tag{4}$$

ENERGY: It provides the sum of squared elements in the GLCM .Also known as the uniformity or the angular second moment.

$$Energy = \sum_{i,j=0}^{n-1} P_{ij}^2 \tag{5}$$

Where P_{ij} is the Grey Level Co-occurrence matrix (GLCM).

E. Classification using Support vector machine

Support vector machine (SVM) [2] is a classification algorithm based on the supervised learning model. In SVM, a high dimensional feature space is divided into two halves by constructing a hyperplane where each half belongs to a different class. Hyperplane is given by the equation:

$$G(x) = w^t x + b \tag{6}$$

Where x is the feature vector, w gives the orientation of the plane, b is the bias i.e. position of the hyper plane w.r.t. origin in high dimensional space. Here values of w and b are optimized by giving training samples from both the classes of image which also maximizes the distance between the two classes, thus forming an accurate classifier. In SVM, feature vector of each class are on either sides of the hyper plane. Class vectors at boundary are called support vectors as the position and orientation of hyper plane depends upon them.

$$G(x_1) = w^t x_1 + b > 0, x_1 \in C_1 \tag{7}$$

$$G(x_1) = w^t x_1 + b < 0, x_1 \in C_2 \tag{8}$$

After training the classifier, a feature vector x_1 is given for testing it. G(x_1) is calculated for the given vector if G(x_1)

value comes out to be positive then x1 belongs to class C_1 and if G(x) comes out to be negative then x_1 belongs to class C_2.

F. Performance Measure

Performance of a classification algorithm can be measured by a specific table layout which is called the Confusion Matrix [9]. It is called so because it makes it easier to see whether the method is confusing the result of classification between the two classes. Each column in confusion matrix shows instances in the predicted class and each row shows instances in the actual class. Confusion matrix is shown in the fig.5.

PREDICTED CLASS			
ACTUAL CLASS		Abnormal	Normal
	Abnormal	TP	FN
	Normal	FP	TN

Fig. 5 Confusion Matrix

Where TP, TN, FP, and FN are given as:

- True Positive (TP): Abnormal brain correctly identified as abnormal.
- True Negative (TN): Normal brain correctly identified as normal.
- False Positive (FP): Normal brain incorrectly identified as abnormal.
- False Negative (FN): Abnormal brain incorrectly identified as normal.

Parameters that are calculated using confusion matrix are:

1. Accuracy = $\dfrac{TP + TN}{TP + TN + FP + FN} * 100$
2. Sensitivity = $\dfrac{TP}{TP + FN} * 100$
3. Specificity = $\dfrac{TN}{TN + FP} * 100$

III. Experimental Discussion

Our method includes following steps: image pre-processing, segmentation, feature extraction, classification. In image pre-processing step, MRI images are first converted from RGB to grayscale and resized to a size of 500 X 500.Then median filter is used to remove noise from the image and to make segmentation accurate.

In segmentation step, Tumour region from an abnormal brain MRI image is extracted leaving behind all other unwanted parts of the image. These steps play an important role as it makes the classification easier and faster. In feature extraction, we have calculated only 5 features for the classification. As the number of features in our feature vector is so small, our method is fast and takes less computational power compared to other methods.

TABLE I

Features Extracted

GLCM FEATURES	NORMAL IMAGE	ABNORMAL IMAGE
Contrast	1.5571 e-04	2.1322 e-04
Correlation	0.8351	0.9737
Homogeneity	0.9999	0.9999
Entropy	-2.3434 e06	-1.1634 e07
Energy	0.99989	0.9917

The classification processing is divided into two parts i.e. training and testing part. In training part, known data (i.e. 5 features*40 images) is given for the training of classifier. After the completion of training, 50 unknown images are given to the classifier for classification, this is the testing part. The classification is performed using SVM. The accuracy of classification mainly depends upon its training part.

IV. Results & Discussion

In this method, we are using brain MRI images of 90 patients. Out of these 90 images, 40 images have been used for training of classifier and other 50 images for testing. Firstly, features calculated from 40 training images have been given to the classifier (based on SVM). After Training, 50 unknown images have been given to the classifier for classification into normal and abnormal. Accuracy, sensitivity and specificity were calculated based on the confusion matrix shown in Table II and they came out be 96%, 92% and 100% respectively. Table III shows the comparison of accuracy of other methods and our method i.e. SVM with segmentation. It shows that accuracy of our method is greater than the method [10] but slightly lower than method [11].

TABLE II

Confusion Matrix

PREDICTED CLASS				
ACTUAL CLASS		Abnormal	Normal	Accuracy
	Abnormal	23/25	2/25	92%
	Normal	0/25	25/25	100%

TABLE III

Comparison of proposed method with other methods used.

REFRENCES	METHOD	ACCURACY
Hari Babu Nandpuru et al [10]	Skull Masking + SVM	84%
Ketan Machhale et al [11]	Skull Masking + SVM-KNN	98%
PROPOSED METHOD	SEGMENTATION + SVM	96%

V. CONCLUSION

This research paper involves using a segmentation technique for the extraction of tumour region in an abnormal image and its classification from normal image using SVM. Results obtained from this method shows that the accuracy attained for classification is 96%. Other advantages of our method are that it is fast and uses small computational power as compared to other methods. For future work, a hybrid SVM algorithm can be used to get better accuracy.

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