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Automated Grade Classification of Brain Tumor MRI

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Abstract

A computer-assisted classification method combining conventional magnetic resonance imaging (MRI) and perfusion MRI is developed and used for differential diagnosis. The proposed scheme consists of several steps including ROI definition, feature extraction, feature selection and classification.The objective of this study is to investigate the use of pattern classification methods for distinguishing different types of brain tumors, such as primary gliomas from metastases, and also for grading of gliomas. The extracted features include tumor shape and intensity characteristics as well as rotation invariant texture features. Features subset selection is performed using support vector machines (SVMs) with recursive feature elimination. The binary SVM classification accuracy, sensitivity, and specificity, assessed by leave-one-out cross-validation on 102 brain tumors.

Keywords- Classification, Feature Extraction, ROI , SVM.

1.Introduction

Clinical data have shown that survival rates vary considerably among brain tumor patients,according to the type and grade of the tumor. Metabolite profiles of intact tumor tissues measured with high-resolution magic-angle spinning proton nuclear magnetic resonance spectroscopy (HRMAS 1H NMRS) can provide important information on tumor biology and metabolism. These metabolic fingerprints can then be used for tumor classification and grading, with great potential value for tumor diagnosis.

Now-a-days the major reason for death among the people is brain tumors. The automated system to identify brain tumors will help the patients in their early diagnosis. Depending on the gradesof the tumor, treatment will vary. Hence the automatic

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classification of brain tumor grades by the system from the brain MRI isessentially a need for the patients for their survival. The proposed system is designed in order to classify the type of tumor based on its features that are extracted from the segmented tumor region of brain image.

Brain tumours are caused by abnormal and uncontrolled growing of the cells inside the brain or spinal canal. The primary tumours are those started in the brain and are categorised in four main types: Gliomas, Meningiomas, Pituitary adenomas and Nerve sheath tumours. The most popular grading system for tumours is that suggested by the World Health Organization (WHO). Regarding to the WHO grading system, the tumours are graded from I to IV, corresponding to least advanced to the most advanced diseases, respectively. Utilizing computer-aided procedures for medical diagnosis and treatment is a growing field of research nowadays. Image processing and pattern recognition algorithms are widely used for analysis and interpretation of medical images.

In this paper a feasibility study of brain MRI dataset classification, using ROIs which have been segmented either manually or through a superpixel based method in conjunction with statistical pattern recognition methods is presented. In our study, 471 extracted ROIs from 21 Brain MRI datasets are used, in order to establish which features distinguish better between three grading classes. Thirty-eight statistical measurements were collected from theROIs. We foundby using the Leave-One-Out method that the combination of the features from the 1st and 2nd order statistics, achieved high classification accuracy in pair-wise grading comparisons. Keywords, Brain tumour grading, MRI images, superpixel segmentation, pattern recognition, SVM classification.

2. RELATED WORKS

Most important and impartible element of classification and pattern recognition tasks. In Brain Tumour Grading in Different MRI Protocols using SVM on Statistical Features Mohammadreza

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Soltaninejad1msoltaninejad@lincoln.ac.uk Xujiong Ye1xye@lincoln.ac.uk Guang Yang 2gyang@sgul.ac.uk Nigel Allinson1nallinson11@gmail.com Tryphon Lambrou1 tlambrou@lincoln.ac.uk1School of Computer Science, University of Lincoln, UK 2St. George's, University of London, UK 2 soltaninejad et al.: brain tumour grading in mri using svm the case of medical images, such as MRI, the reduction of dimensionality is of high importance.

MRI images are three-dimensional volumetric data acquired with different protocols, which lead to extraction of high dimensional information in the form of statistical features. Classification of high dimensional data is based on these extracted features. Several techniques have been used to detect and classify brain tumours in MRI images. Joshi etal. [1] developed a system for detection of Astrocytoma cancer tumours and classify them base on artificial neural network. They use grey-level co-occurrence matrix for texture feature selection and Neuro-Fuzzy classifier to classify the tumours. Georgiadis et al. [2] proposed a method to classify primary tumours and metastatic, which are originated outside brain. They applied non-linear least square feature transformation and combined it with a probabilistic neural network (PNN).

Zacharaki et al. [3] used SVM with recursive feature elimination for classification of tumour grades in MRI images using texture, shape and rotation invariant texture features. They suggested one-versus-all SVM classification and majority voting for multi-class problem. In this paper, we intend to classify tumour grades II, III and IV using different MRI acquisition protocols i.e. FLAIR, and T2. Region of interest segmentation is performed separately for each protocol. The segmentation is based on a superpixel based method with nearly similar intensity features. Then 1storder and 2ndorder statistical textural features are extracted.

Sandeep et al. (2006)developed the neural network and support vector machine classifiers for the classification of brain images. Features

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extracted using wavelets are fed as inputs to the neural network classifier. Discrete Wavelet Transform uses the discrete set of wavelets to implement the wavelet transform[15]. SVM is the binary classification method that takes input from two classes and produces the output as the model file for the classification of data into the corresponding classes. Neural network is the non-linear computational unit through which large class of patterns can be recognized. The performancesof both these classifiers are evaluated and based on this neural network is found to be the efficient classifier.

Arthi et al.(2009) [1], proposed the hybrid of neural network and fuzzy technique for the diagnosis of hyperactive disorder. A combination of self organizing maps which is unsupervised technique and radial basis function which is supervised algorithm. In Self Organizing Map, learning process is carried out and learning parameter rate starts to decrease during the convergence phase. Radial Basis Function neural network is a supervised technique for the non-linear data and in this no hidden layer units are present. Based on the degree of sensitivity to inputs, the hidden units in neural network are assigned with equal weights. They concluded that hybridization of these methods involves complexity and relaxation of training dataset is not possible in such scenarios.

Deepa and Aruna Devi (2012)compared the performance of BPN and RBFN classifier for the classification of MR brain images. They simply found whether the brain image is normal or abnormal and they have not found out its grades if it is tumorous. They concluded that RBFN classifier is best suited for the classification of brain tumors.

The aim is to classify the tumours using the features collected from every individual protocol as well as their combinations. For this task, a support vector machine (SVM) classifier is utilized to classify different combinations of the data. The evaluation is performed using the overall classification accuracy and comparison of the results.

2.1 Outline Work

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In this paper A classification techniques based on Support Vector Machines (SVM) are proposed and applied to brain image classification segmentation. The feature extraction from MRI Images will be carried out by gray scale, symmetrical and texture features. The main objective of this system is to give an excellent outcome (i.e. higher accuracy rate and lower error rate) of MRI brain cancer classification using SVM. The extraction of texture features in the detected tumor has been achieved by using Gray level co-occurrence matrix (GLCM) and Gabor Filters .

This Paper is organized as follows. Section 3 describes related research,Section 4 outlines the proposed method , feature extraction , classification. In section 5 Post Processing ,Morpological operations,Region growing algorithms and experimental results are discussed. The conclusion are given in section 6.

3.Proposed Method:

The architecture of the proposed is illustrated in Figure 1.The major components are Brain tumor Database, Pre processing , Feature extraction and Classification.

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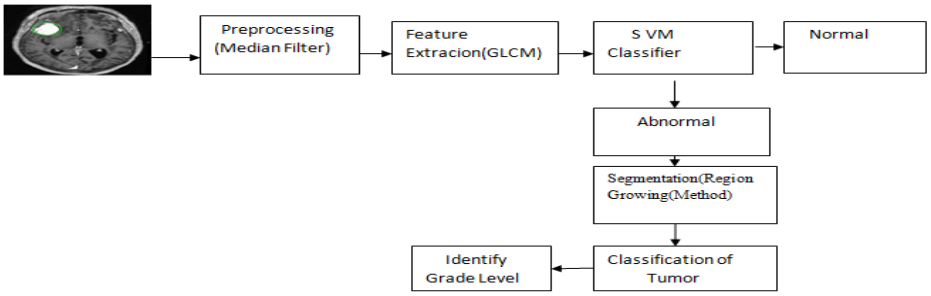

Fig 1.Outlined of the Proposed Method

3.1 Preprocessing

3.2 Feature Extraction

Gray-level co-occurrence matrix (GLCM) is a statistical method of finding the textures that consider the spatial relationship of the pixels. The GLCM functions characterize the texture of an image by evaluating how frequently pairs of pixel with specific values occur in a specified spatial relationship present in an image, [GLCM [3]]. This makes the extraction of statistical measures from this matrix possible. It is the most widely used and more generally applied method because of its high accuracy and less computation time. A gray level cooccurrence matrix (GLCM) contains information about the positions of pixels having similar gray level values [10].The five features extracted in this paper are explained below.

(i) Mean:

The mean is defined as below

$$\text{Mean(m)}=\frac{1}{x+1}\sum_{i=1}^{x}\sum_{j=1}^{y}x(i,j) \quad (1)$$

(ii) Variance:

It is square of Vaiance. The Variance is defined as below

$$\text{Variance(v)}=\frac{1}{x+1}\sum_{i=1}^{x}\sum_{j=1}^{y}(x(i,j)-m)^2 \quad (2)$$

(iii) Entropy:

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

$$\text{Entropy}=\sum_{i=1}^{N}\sum_{j=1}^{N}\left(\frac{(u(i,j))}{R}\right)log\frac{(u(i,j))}{R} \quad (3)$$

(iv) Contrast:

Contrast is defined as the separation between the darkest

and brightest area.

$$\text{Contrast}=\sum_{i=1}^{N}\sum_{j=1}^{N}(i-j)^2\left(\frac{p(i,j)}{R}\right) \quad (4)$$

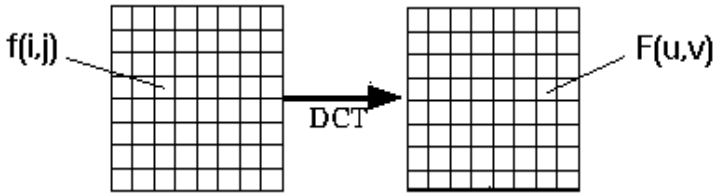
(v) Energy:

It provides the sum of squared elements in the GLCM. The uniformity or the angular second moment are also identified.

$$\text{Energy}=\sum_{i=1}^{N}\sum_{j=1}^{N}\left(\frac{u(i,j)}{R}\right)^2 \quad (5)$$

3.2.1 The Discrete Cosine Transform (DCT)

The discrete cosine transform (DCT) helps separate the image into parts (or spectral sub-bands) of differing importance (with respect to the image's visual quality). The DCT is similar to the discrete Fourier transform: it transforms a signal or image from the spatial domain to the frequency domain.



DCT Encoding

The general equation for an 1D (*N* data items) DCT is defined by the following equation:

$$F(u)=\left(\frac{2}{N}\right)^{\frac{1}{2}}\sum_{i=0}^{N-1}A(i).\cos\left[\frac{\pi.u}{2.N}(2i+1)\right]f(i) \quad (6)$$

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and the corresponding *inverse* 1D DCT transform is simple $F^{-1}(u)$, i.e.:

where

$$A(i) = \begin{cases} \frac{1}{\sqrt{2}} & for \in = 0 \\ 1 & otherwise \end{cases} \quad (7)$$

The general equation for a 2D (*N* by *M* image) DCT is defined by the following equation:

$$F(u,v) = \left(\frac{2}{N}\right)^{\frac{1}{2}} \left(\frac{2}{M}\right)^{\frac{1}{2}} \sum_{i=0}^{N-1} \sum_{j=0}^{M-1} A(i).A(j).\cos\left[\frac{\pi.u}{2.N}(2i+1)\right] \cos\left[\frac{\pi.u}{2.M}(2j+1)\right].f(i,j) \quad (8)$$

and the corresponding *inverse* 2D DCT transform is simple $F^{-1}(u,v)$, i.e.: where

$$A(\in) = \begin{cases} \frac{1}{\sqrt{2}} & for \in = 0 \\ 1 & otherwise \end{cases} \quad (9)$$

The basic operation of the DCT is as follows:

- The input image is N by M;
- f(i,j) is the intensity of the pixel in row i and column j;
- F(u,v) is the DCT coefficient in row k1 and column k2 of the DCT matrix.
- For most images, much of the signal energy lies at low frequencies; these appear in the upper left corner of the DCT.
- Compression is achieved since the lower right values represent higher frequencies, and are often small - small enough to be neglected with little visible distortion.
- The DCT input is an 8 by 8 array of integers. This array contains each pixel's gray scale level;
- 8 bit pixels have levels from 0 to 255.
- Therefore an 8 point DCT would be:

where

$$A(\in) = \begin{cases} \frac{1}{\sqrt{2}} & for \in = 0 \\ 1 & otherwise \end{cases} \quad (10)$$

3.2.2 Discrete Wavelet Decomposition

The wavelet is a powerful mathematical tool for feature extraction, and has been used to extract the wavelet coefficients from MR images. Discrete Wavelet Transform is an implementation

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of the WT using dyadic scales and positions. The basic fundamental principle of DWT is as follows: Suppose $x(t)$ is a square-integrable function, then the continuous WT of $x(t)$ relative to a given wavelet $\Psi(t)$ is defined as, $\int$ (1) where, the wavelet is calculated from the mother wavelet $\Psi(t)$ by dilation and translation factor a and b respectively, which are real positive numbers. The *DS* operator is used for down sampling. two dimensional DWT results in four sub bands LL (low-low), LH (low-high), HL (high-low), HH (high-high) at each scale. Sub band LL, is the approximation component of the image, which is used for the next two dimensional DWT. whereas, LH, HL, HH are the detailed components of the image along the horizontal, vertical and diagonal axis, respectively, as shown in the figure 3.

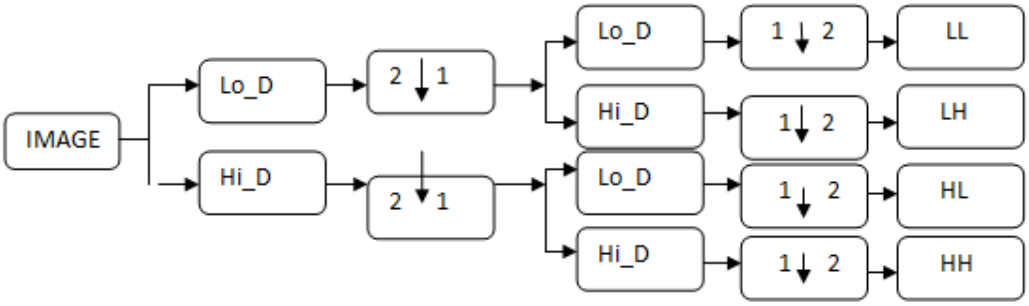

fig.2 Discrete Wavelet Transform taken from [15]

Lo_D – Low Pass Filter Ho_D – High Pass Filter

Based on the literature study, Daubechies wavelet is considered the best among wavelets for image application and LH, HL sub-bands had higher performance compared to the features from LL sub band. Hence in this method, a five level decomposition using the daubechies wavelet was computed and the features were extracted from LH and HL sub bands formed using DWT.

3.3 Classification:

The Proposed method is considered superior over SVM and other neural networks in terms of accuracy in classification.It is employed to implement an automatic MR image classification of brain tumors into normal, abnormal .It automatic Classification of Brain MRI Using Region Growing method and SVM.

3.3.1Support Vector Machine

Support vector machines are a state of the art pattern recognition technique developed from statistical learning theory. The basic idea of applying SVMs for solving classification problems can be stated briefly as follows: a) Transform the input space to higher dimension feature space through a non-linear mapping function and b) Construct the separating hyperplane with maximum distance from the

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closest points of the training set. In the case of linear separable data, the SVM tries to find, among all hyperplanes that minimize the training error, the one that separates the training data with maximum distance from their closest points

$$w.x + b = 0 \quad (11)$$

when w and b are weight and bias parameters respectively.The optimization problem is solved using the MATLAB optimization toolbox the Support Vector Machine(SVM) is employed to implement an automated brain tumor classification. The performance of the SVM classifier is evaluated in terms of training performance and classification accuracies. Tumor area is calculated. Finally there is a comparison to the accuracy of Discrete Cosine Transform (DCT) and Discrete Wavelet Transform (DWT) over 102 MRI of the brain. Simulation is performed by MATLAB 13a software.

3.4 Post Processing

The major components of the system are Morpological operations,Erosion ,dilation and Region Growing Method, experimental results and performance analysis are discussed below.

3.4.1 Morphological Operations:

In this paper morphological operators are used for the tumor region extraction and to further remove the nontumor regions. In tumor regions, vertical edges, horizontal edges, and diagonal edges are mingled together while they are distributed separately in non tumor regions [9]. The dilation operator is used for filling the broken gaps and to have continuities at the boundaries. Binary Dilation and Erosion The set of black and white pixels constitute a description of a binary image. Assume that only black pixels are considered, and the others are treated as a background. The primary morphological operations are dilation and erosion, and from these two, more complex morphological operations such as opening, closing, and shape decomposition can be worked out.

3.4.2 Dilation

The dilation operation thickens the image. The extent of thicken imege is dependent on the structuring element. The structuring element is a part of the image.The morphological transformation dilation (+) combines two sets using vector addition.The dilation operation can be done by performing vector addition of the pair of elements for both the sets X and B.

Example:

$$X = \{(1,0),(1,2),(1,2),(2,2),(0,3),(0,4)\}$$
$$B = \{(0,0),(1,0)\}$$
$$X(+)B = \{(1,0),(1,2),(1,2),(2,2),(0,3),(0,4),(2,0)\ (2,2$$

3.4.3 Erosion

The erosion operation performs either shrinking or thinning of the object. The extent of this operation is decided by the structuring element.Erosion (-) combines two sets using vector subtration of set elements is the dual operator of dilation. Neither erosion nor dilation is an invertible transfomation.

Example:

$$X = \{(1,0),(1,2),(1,2),(2,2),(0,3),(0,4)\}$$
$$B = \{(0,0),(1,0)\}$$
$$X(-)B = \{(0,3),(1,3),(2,3)\}$$

3.5 Region Growing Method

There are a few important pointer to be considered when trying to segment an image. are

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must have regions that are disjointed because a single point cannot be contained in two different regions. The regions must span the entire image because each point has to belong to one region or another. To get regions,one must define some property that will be true for each region defined. To ensure that the regions are well defined and that they are indeed regions themselves and not several regions together or just a fraction of a single region, that property should not be true for any combination of two or more regions. If these criteria are met, then the image is truly segmented into regions. This paper discusses two different region determination techniques: one that focuses on edge detection as its main determination characteristic and another that uses region growing to locate separate areas of the image.

4.Experimental Results

4.1 MRI image data set

For the classification and segmentation of normal and abnormal brain images, data set is collected from different sources. One of the sources is the Harvard Medical School Website.
[http://www.med.harvard.edu/aanlib/home.html]
The types of brain images include Axial, T2-weighted, 256-256 pixels MR brain images. Figure 3 shows one of the databases considered for classification. The images are classified as normal and abnormal.

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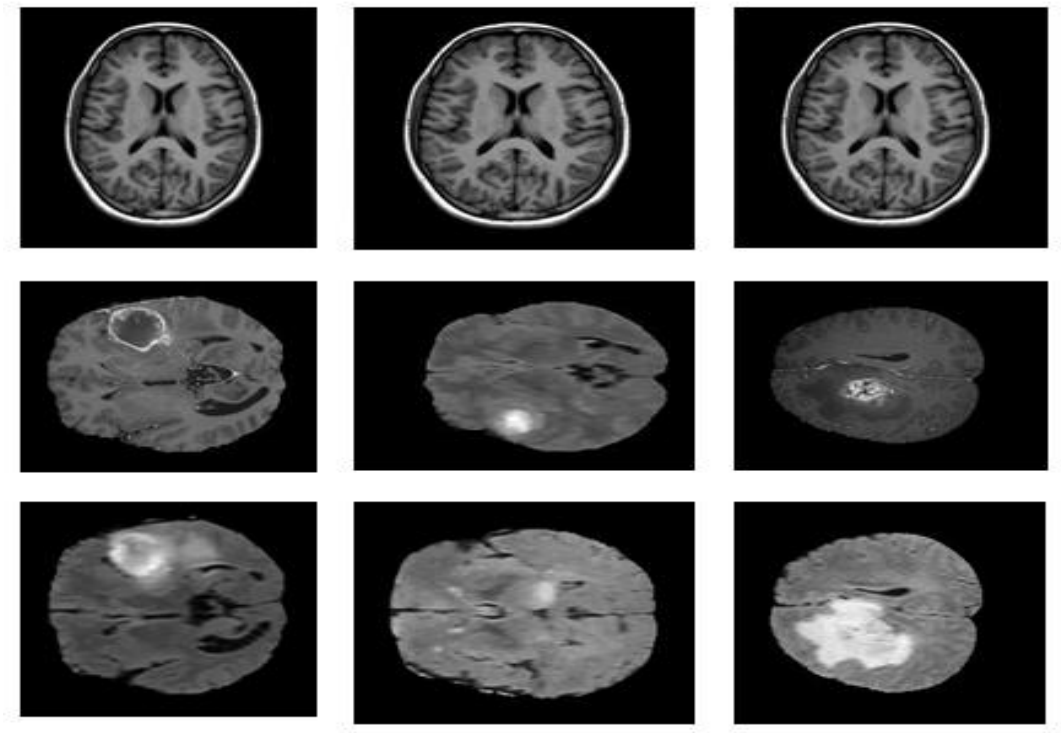

Figure 3. MRI of the human brain. (a) - (c) Normal. (d) - (f) Meaningiomas

(g) - (i) Asstrocytomas

4.2 Performance Evaluation

The comparison was done with testing techniques according to the following performance measures

OurHybrid Techniques	Normal	Tumor
Normal	TP	FP
Tumor	FN	TN

Table 1: Testing Techniques for Performance Anaysis

$$True\ positive = \frac{No.of\ results\ images\ having\ Brain\ Tumor}{Total\ No.of\ images} \quad (12)$$

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$$True\ Negative = \frac{No.of\ images\ that\ haven't Brain\ Tumor}{Total\ No.of\ images} \quad (13)$$

$$False\ positive = \frac{no.of\ images\ that\ haven't tumor\ and\ detected\ positive}{total\ no\ of\ images} \quad (14)$$

$$False\ negative = \frac{no.of\ images\ have\ tumor\ and\ not\ detected}{total\ no\ of\ images} \quad (15)$$

Type equation here.

To compute *F*-measure,

$$F - measure = 2PR/(P+R) \quad (16)$$

where, P and R are precision and recall. The *F*-Measure computes the average information retrieval precision and recall metrics. Precision is calculated using following equation,

$$Precision = TP/(TP+FP) \quad (17)$$

where, TP and FP are True Positive and False Positive. Recall are calculated using the equation

$$Recall = TP/(TP+FN) \quad (18)$$

where, TP and FP is True Positive and False Positive. TP is the total number of correctly detected Brain tumors. FP is total number of in-correctly detected Brain tumors. False Negative (FN) represents the total number false detections.
using the equation

$$Speciticity = TN/(TN+FP) \quad (19)$$

where, TN and FP are True Negative and False Positive. Specificity calculated using the equation

$$Accuracy = (TP+TN)/(TP+FP+FN+TN) \quad (20)$$

4.3 Experimental Results for tumor detection

The image datasets were implemented (Matlab 20013a) for SVM and ROI, tested and compared. Each algorithm was trained and tested for each dataset, under the same model (kernel with the corresponding parameters) in order to achieve the same accuracy. In order to evaluate the classification efficiency, two metrics have been

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computed: (a) the training performance (i.e. the proportion of cases which are correctly classified in the training process) and (b) the testing performance (i.e. the proportion of cases which are correctly classified in the testing process). Basically, the testing performance provides the final check of the SVM classification efficiency, and thus is interpreted as the diagnosis accuracy using the ROI support.

Table II: Features extracted using GLCM

Images	Contrast	Correlation	Homogeneity	Energy	Entropy
Brainim1	0.1181	0.9195	0.9978	0.9680	0.2367
Brainim2	0.1068	0.9167	0.9781	0.9512	0.2895
Brainim3	0.1174	0.9098	0.9812	0.9487	0.2510
Brainim4	0.1126	0.9201	0.9645	0.9432	0.2712
Brainim5	0.1082	0.8955	0.9651	0.9827	0.2619
Brainim6	0.1149	0.9189	0.9806	0.9715	0.2761

TableII shows the features of the MR brain images extracted using GLCM and this is the sample dataset. Based on those features only the classifier is trained. The performance of the classifier can be estimated using the following equations:

Sensitivity (true positive fraction) = TP/TP+FN
Specificity (true negative fraction) = TN/TN+FP
Accuracy = TP+TN/TP+TN+FP+FN
Recall=TP=(TP / FN)

Table III: Performance of SVM

SVM	Actual Value		
	Normal	Abnormal	Total
Prediction	TP=14	FP=7	21
FN	FN=3	TN=18	21
Total	17	25	42

Table IV: Performance of ROI

ROI	Actual Value		
	Normal	Abnormal	Total
Prediction	TP=15	FP=4	19
FN	FN=2	TN=21	23

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Total	17	25	42

The input data involved 42 patients (25 abnormal and 17 normal).The numbers of normal images for training set is 30 whereas for abnormal images are 12.

Table V: Comparison of classifiers

Indices	SVM	ROI
Accuracy	76.19	85.09
Sensitivity	82.3	76
Specificity	88.23	86.75
Recall	78.9	83.2

The methodology of Region Growing was applied of MR brain tumor images of the head to obtained segmented regions of tumor. The performance was evaluated. The Classification results are displayed below in Fig 3(a) and (b).The classification gets closer as the number of training samples increases; the pattern layer consists of a processing element corresponding to each input vector in the training set. All the output parameters in the pattern layer is tested and trained based on SVM values. An element is trained to return a high output value when an input vector matches the training vector. Accuracy analysis are shown in the following figure:

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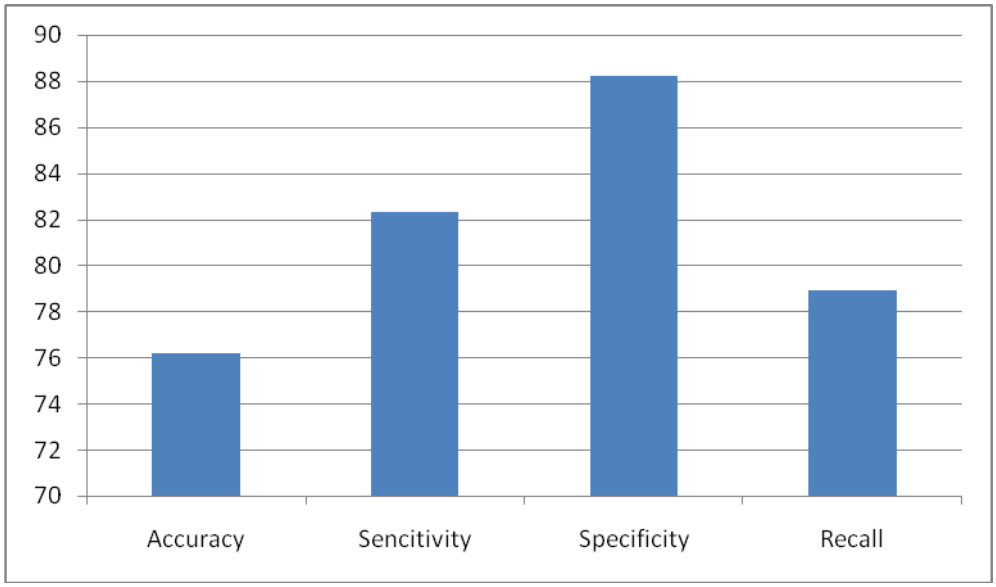

Fig. 4 Performance analysis for SVM Classifiction

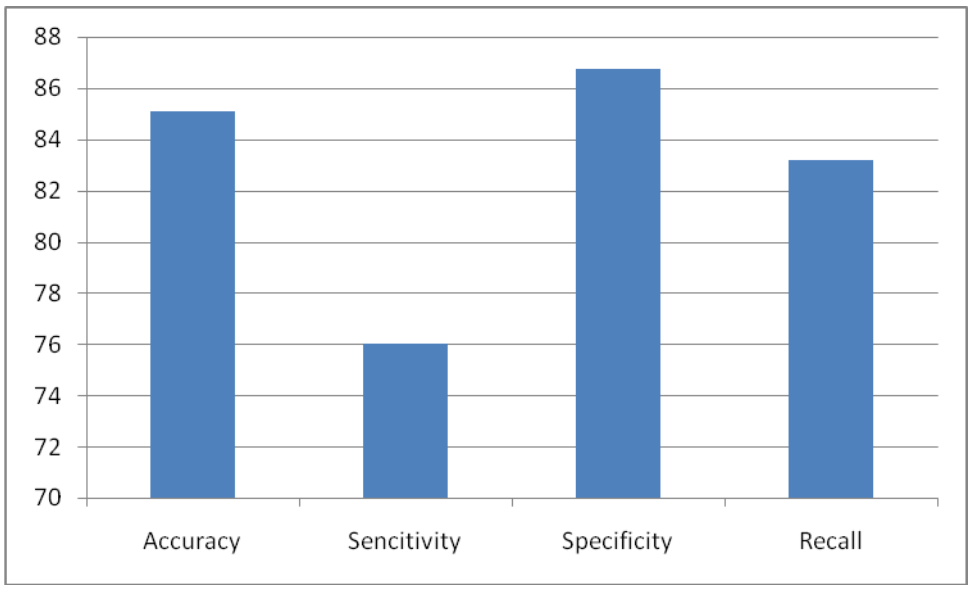

Fig. 5 Performance analysis for ROI Classifiction

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5.Conclusion and Future work

The automated classification of brain tumor grades using various neural network classifiers is discussed. The performance of these classifiers on the collected data set is measured using sensitivity, specificity and accuracy. The accuracy of the classifier mainly depends on the optimal features based on which it is trained. The problem is in selecting the optimal features to distinguish between the classes. More optimization requires the selection of best feature subset. Algorithm extensions can be done by incorporating the spatial autocorrelation byfusion at different levels which reduces the mean square error in each case.

Further research issues can be improved using kernel caching techniques and moment features can also be extracted to classify the different grades of the tumor. It appears that ANN could be a valuable method to statistical methods.

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