ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 5, May 2016

Multiclass Classification of Brain Tumor in MR Images

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ABSTRACT: Brain tumor is one the major cause of death among all other types of cancer during these days. Proper diagnosis can prevent the life of patient to some extent. MRI is the widely used technique, in detecting the brain tumor. Although numerous brain tumor segmentation and classification methods have been presented, enhancing tumor segmentation methods and multiclass classification is still challenging due to complex characteristics of brain tumor, such as high diversity in tumor appearance and ambiguous tumor boundaries. To address this problem we propose the novel multiclass classification method for MRI image. Proposed system is a multi-stage system for brain tumor diagnosis and tumor region extraction. First, noise removal, skull striping and intensity normalization is performed as the preprocessing step on the brain MR images. Texture and intensity features are extracted from these noise free brain MR images. Next phase of the proposed system is multiclass classification that is based on these extracted features. This method uses multiclass Support Vector Machine (SVM) to classify five types of tumor based on the WHO grading system i.e Astrocytoma(Grade-I), Glioblastoma Multiforme(Grade-IV), Meningioma(Grade-II), Medulloblastoma (Child tumor) (Grade-IV) and metastatic melanoma(Grade-III). The result shows that it gives 76.14% accuracy in Astrocytoma , 76.65% in Glioblastoma, 86.60% in Medulloblastoma, 84.26% in Meningioma and 82.23% in Metastatic Melanoma which is acceptable accuracy.

KEYWORDS: Brain Tumor; Magnetic Resonance Image(MRI); Regularization; Supervised Learning.

I. Introduction

With the growing extent of aging population, cancer has become a global public health problem. According to the World Cancer Research Fund's latest statistics , cancer is the world's first cause of death. There is 14.1 million cancer cases around the world and it is expected to increase to 24 million by 2035[22].

Brain tumor is the uncontrolled growth of the abnormal tissue in brain or the central spin that can disrupt the normal brain function. Brain tumor can be classified into two types based on the origin of the tumor and whether they are cancerous or not. Two types of brain tumor are Benign(Primary) and Malignant(Secondary or Metastatic). Fig 1 shows the detailed types of tumor.

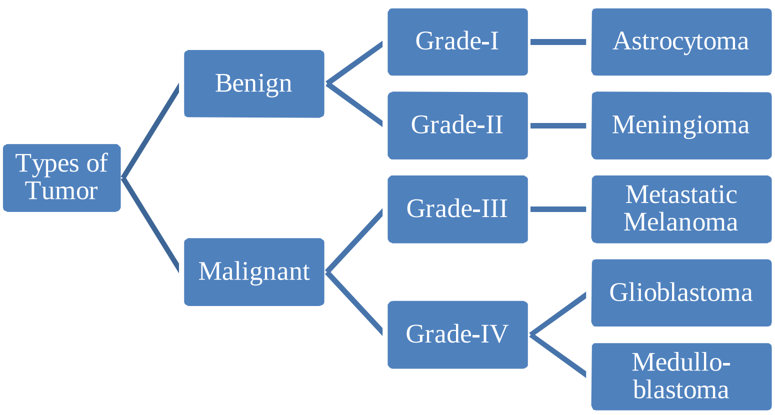

Fig. 1. Types of Brain Tumor

ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

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Vol. 4, Issue 5, May 2016

Benign tumors are least aggressive that originate in the brain and do not consist of cancerous cells. This type of tumor grows slowly and are curable. Malignant tumors have cancerous cell that originate anywhere in the body and spread to the brain. This type of tumor has rapid growth and do not have the clear boundaries.

The World Health Organization (WHO) issued the most widely used grading scheme that classifies the tumor in four grades. In that grading scheme grade I and grade II tumors are considered as benign brain tumor (low-grade) and grade III and grade IV are considered as malignant brain tumor (high-grade)[1]. Further World Health Organization (WHO) has defined the specific types of primary tumors and secondary tumors. Astrocytoma and Meningioma are primary types of tumor and Glioblastoma Multiforme, Medulloblastoma and Metastatic Melanoma are the secondary types of tumor[23].

Image modalities plays an important role in brain tumor detection. There are various imaging modalities available such as Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET) and Magnetic Resonance Spectroscopy (MRS) which provides the exact characteristics about tumor metabolism and morphology[2].

CT uses the radioactive rays to penetrate the human body, and the imaging is based on the different characteristics reflecting to the rays of different tissues. PET needs to inject with radioactive drugs in the human body, and the drugs will flow to all the cells, tissues and organs with the blood in the whole body. The absorbed radiation will be metabolized and released by different tissues to form different rays which can be received for a specific imaging.

CT/PET refers to the combination of CT and PET scans which are carried out on the same plane to form a fused image with the machine. Both CT and PET examination have radioactive hazards, and PET examinations are too expensive. Compared with all these imaging modalities above, MRI is the most cost-effective [6].

In the MRI imaging process there will be not any instruments entering and any medication injected into the human body. There is not any radiation damage to the human body, and the whole process is quite safe. In addition, MRI imaging has high-resolution and accurate positioning of soft tissues, and is sensitive to the characteristics of diseases, thus it is specially suitable for the diagnosis of brain diseases.

Magnetic Resonance Imaging (MRI) is the standard and non-invasive technique that provides good information about tumor size, shape and localization. In clinics, various types of MRI sequences are used to diagnose the tumor. These image sequences incorporate five types i.e. T1-weighted MRI (T1w), T1-weighted MRI with contrast enhancement (T1wc), T2-weighted MRI (T2w), Proton Density-weighted MRI (PDw), Fluid Attenuated Inversion Recovery (FLAIR), Fig. 2 shows the four standard sequences of glioblastoma (a type of brain tumor) patient[1].

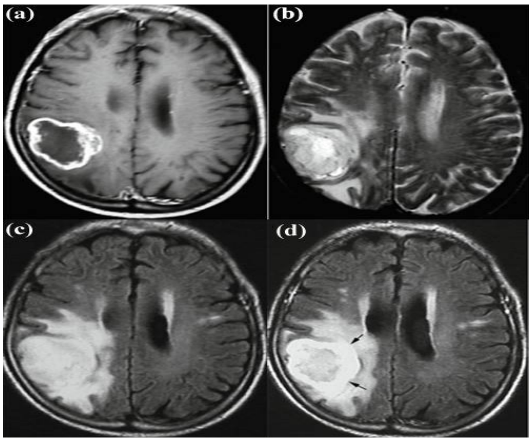

Fig. 2. Four imaging modalities: (a) T1-weighted; (b) T2-weighted; (c) FLAIR; (d) FLAIR with contrast Enhancement[1].

The 2012 CBTRUS (Central Brain Tumor Registry of the United States) Statistical Report has also showed that brain tumors are the second leading cause of cancer related deaths in children under age 20 and the most common cancer among those age 0-19. Nearly 78,000 new cases of primary brain tumors are expected to be diagnosed this year which includes nearly 25,000 primary malignant and 53,000 non-malignant brain tumors. Meningioma represent 36.4% of all primary brain tumors. There will be an estimated 24,880 new cases in 2016. Glioblastoma has the highest number

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ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

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of cases of all malignant tumors, with an estimated 12,120 new cases predicted in 2016. Astrocytoma, including glioblastoma, represent approximately 75% of all glioma. Medulloblastoma/embryonal/primitive tumors represent 1% of all primary brain tumors. The majority of primary tumors (36.4%) are located within the meninges[24].

There are mainly four basic steps in brain tumor detection as shown in Fig. 3.

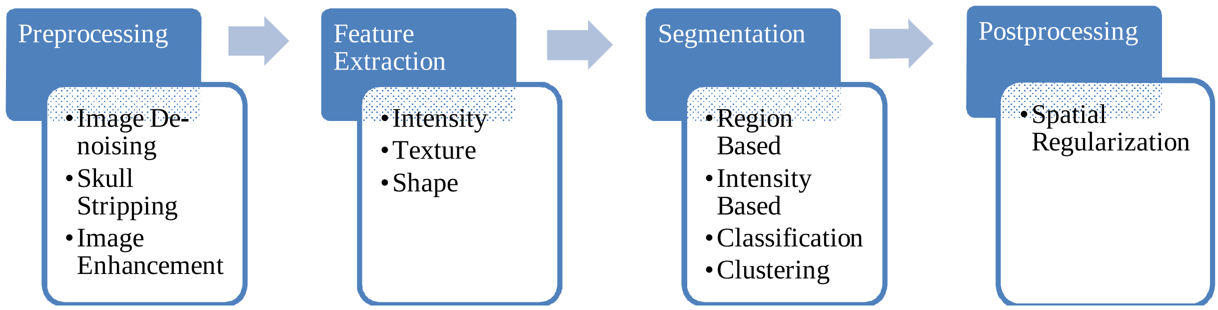

Fig. 3. Steps for brain tumor detection

A. *Pre-processing:*

Preprocessing gives the finer image from raw MRI image. So preprocessing is directly related to the quality of segmentation result. These pre-processing operations include de-noising, skull-stripping, image enhancement etc.[1].

B. *Feature Extraction:*

Feature extraction is a method to transform an image into its set of features[3]. To segment the brain tumor accurately, feature extraction is the fundamental task. For medical images, important features are texture , colour , shape, intensity etc.[2].

C. *Segmentation:*

Segmentation is the method to differentiate the abnormal brain tissues i.e. active cells, necrotic core, and edema (Fig. 4) from normal brain tissues[1]. Based on the requirement of human interaction brain tumor segmentation methods classified into three main types that includes manual , semi automatic and fully automatic segmentation[1]. For tumor detection various segmentation methods available that includes intensity based methods, region based methods, asymmetry based methods and machine learning techniques[4]. Sometimes segmentation problem is considered as a classification problem for classifying normal and abnormal brain MRI slices, for classification purpose various machine learning techniques are used[7].

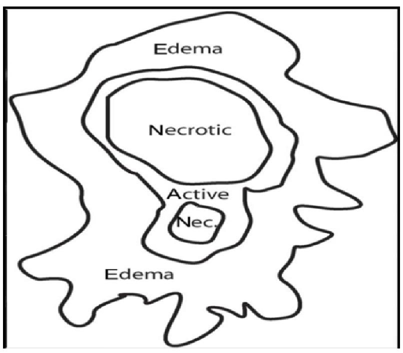

Fig. 4. Three main components of abnormal brain tissue[1].

D. *Post-Processing:*

This includes various post processing technique for better result such as spatial regularization, shape constraints and local constraints[2].

The rest of this review is organized as follow: In Section II contains the related work, section III describes the proposed algorithms for multiclass classification, section IV contains the simulation results and finally conclusion and future is specified in section V.

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II. RELATED WORK

Classification algorithms are popular method of the supervised learning. In this method well trained classifiers like Support Vector Machine(SVM),Artificial Neural Network(ANN) ,extract the important features from the training data and then segment the testing data as per provided feature space. However these methods classify each pixel without considering the spatial correlation between the neighborhood pixel [5],[7],[14]-[16]. So these method will not give globally optimized result. To overcome this issue regularization step added as post-processing. Regularization can be achieved by the variants of random fields i.e. Markov Random Field(MRF) , Conditional Random Field(CRF) [14]-[16]. In [5], authors have used Support Vector Machines (SVM) to classify the brain MRI slices to check whether it is normal or abnormal. In this paper they have used gray scale features, symmetry based features and the texture features. A. Padma and R. Sukanesh have carried out their study on SVM Based Classification of Soft Tissues in Brain CT Images and they have used Wavelet Based Dominant Gray Level Run Length Texture Features. They have concentrated on the CT imaging modality which is widely used and reliable technique for detection of pathological changes using SVM. They obtained 98% accuracy [17]. In [18] comparative analysis of the ANN and SVM is shown. In this study, ANN provide good result to the large amount of features but it will not give the generalized result but in SVM, we can get better accuracy even with the smaller training dataset. It can handle more number of features than the ANN. Above studies have one limitation of multiclass problem i.e. it cannot classify the data in multiple classes. In [4], authors have proposed local independent projection based classification which solves the multiclass problem of binary classifiers but it will done classification in different regions of brain tumor like edema, necrosis, active region etc. In [19]-[21], various methods for multiclass classification i.e. one-vs-all, all together, one-vs-one, Direct Acyclic Graph SVM(DAGSVM) are discussed and from that one-vs-one and DAGSVM are most likely methods for multiclass classification.

III. PROPOSED ALGORITHM

The proposed system developed to help radiologists for classifying brain tumors in MR images. This system classify the tumor types based on its severity i.e. primary or secondary. The block diagram of proposed system is given in fig. 5. The system consist of three basic stapes for classifying the five different types of tumor. (i) Feature extraction methods for tumor classification (ii) Generation of feature space and training database (ii) Multiclass SVM classifier to classify the five types of tumor.

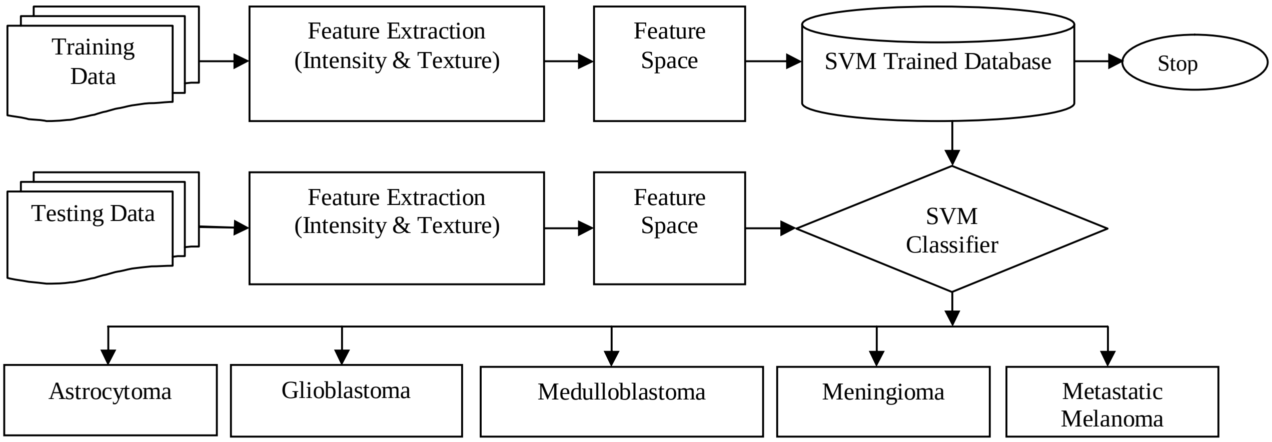

Fig. 5. Proposed Block Diagram for Tumor Classification

In this study, 394 brain tumor MRI mages are used as a dataset which is provided by National Cancer Society. These MR images includes 80 images of Astrocytoma , 80 images of Glioblastoma , 80 images of Medulloblastoma , 80 images of Meningioma and 74 images of Metastatic Melanoma. Now from these training dataset intensity and texture features are extracted using colour moment , gabor filter and wavelet transform. In this study total 94 features are used in which 44 features are gabor features, 6 are colour moments and 44 are wavelet features are detected. These features are converted to higher dimensional feature space.

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International Journal of Innovative Research in Computer and Communication Engineering

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This feature space given as a input to the SVM classifier. SVM classifier employs one-against-one approach for multiclass classification. After classification, segmentation of tumor region is performed for finding the exact size of the brain tumor. Hence these will also gives the severity of brain tumor.

A. *Feature Extraction Techniques:*

Feature extraction gives the features on the basis of which brain MRI images can be easily classified as normal or abnormal. The features which are used for the segmentation of brain tumors largely depend on the type of tumor and its grade because different tumor types and grades have a lot of variability in appearance (e.g. intensity, shape, regularity, location, etc.)[2]. Here we have used mainly texture and intensity features for classification of five types of tumor that explained below.

1. **Color Moments(Intensity):** Color is a widely used important feature for image representation. This is very important as it is invariant with respect to scaling, translation and rotation of an image. Color space, color quantification and similarity measurement are the key components of color feature extraction.

   The mean, variance and standard deviation of an image are known as color moments. Following equations define the mean, variance and standard deviation of an image of size $n \times m$[9].

$$\text{mean} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{m} x_{ij}}{mn} \tag{1}$$

$$\text{variance} = \frac{1}{mn}\sum_{i=1}^{n}\sum_{j=1}^{m}(x_{ij} - \text{mean})^2 \tag{2}$$

$$\text{stddev} = \sqrt{\text{variance}} \tag{3}$$

   where x_{ij} is the Pixel value of the ith row and jth column.

2. **Gabor Transform (Texture):** Gabor filter is the texture descriptors introduced by Gabor in 1946. It is used to extract texture features by analyzing image in frequency domain. Basically, Gabor filter is a Gaussian function modulated by complex sinusoidal of frequency and orientation. It has the ability to perform both in spatial and frequency domain. It can be work in any number of dimensions[10]. A two dimensional Gabor function $g(x, y)$ and its Fourier transform $G(u, v)$ can be written as[11]:

$$g(x, y) = \left(\frac{1}{2\pi\sigma_x\sigma_y}\right)\exp\left[-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2}\right) + 2\pi jWx\right] \tag{4}$$

$$G(u, v) = \exp\left\{-\frac{1}{2}\left[\left(\frac{u - W^2}{\sigma_u^2} + \frac{v^2}{\sigma_v^2}\right)\right]\right\} \tag{5}$$

   Gabor wavelet forms a complete but non-orthogonal basis set that expands signal and provides the localized frequency descriptors which are referred as Gabor Wavelets . The non-orthogonality implies that there will be redundant information in the output data.

   For a given image $I(x, y)$ Gabor wavelet transform is define as

$$W_{mn}(x, y) = \int I(x_1, y_1)g_{mn}^{*}(x - x_1, y - y_1)dx_1dy_1 \tag{6}$$

   Where * indicates the complex conjugate. Feature vector can be constructed using mean μ_{mn} and standard deviation σ_{mn} which can be define as

$$\mu_{mn} = \iint |W_{mn}(xy)|\, dxdy \tag{7}$$

$$\sigma_{mn} = \sqrt{\iint (|W_{mn}(xy)| - \mu_{mn})^2\, dxdy} \tag{8}$$

3. **Wavelet Transform (Texture):** Wavelet transform is a series expansion technique that represent the signal at different levels of resolution[12]. Discrete Wavelet Transform decompose the image in the four sub band images and they are low-low (LL), low-high (LH), high-low (HL) and high-high (HH) channels. The energy within each sub band image is used as feature[8].The major problem in traditional wavelet transform, i.e.

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DWT and CWT, is they are not invariant to translation. To overcome this problem Demirhan et al.[13] used the Stationary Wavelet Transform (SWT) which is invariant to translation. Translation-invariance is achieved by removing the downsamplers and upsamplers in the DWT and upsampling the filter coefficients by a factor of 2^{j-1} in the jth level of the algorithm. The complexity of SWT is directly proportional to number of samples. We can obtain statistical parameters such as energy, entropy, mean absolute deviation and standard deviation as a textural feature[13].

B. *One-against-one approach:*

The one-against-one method constructs all possible pair wise hyperplanes, where each hyperplane is constructed using the training examples from two classes chosen out of k classes. Fig. 6 shows one-against-one classification approach for multiclass classification[19].

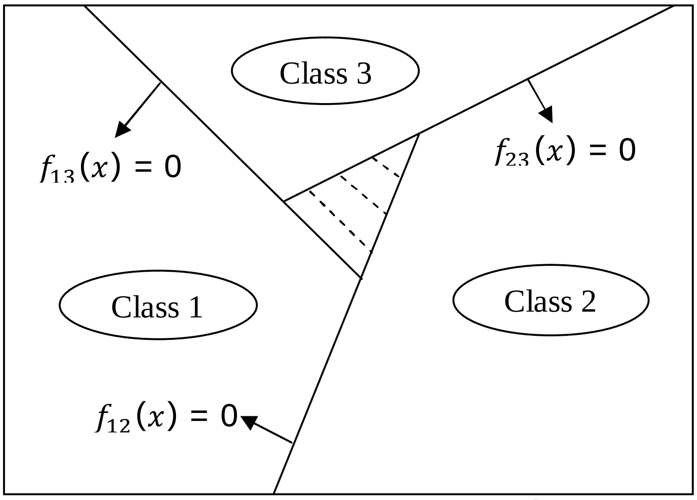

Fig. 6. One-against-One Approach

The decision function for any class pair ij , chosen from k classes, can be defined as

$$f_{ij}(x) = \langle \phi(x).W^{ij} \rangle + b^{ij} \tag{9}$$

It is found by solving the following optimisation problem:

$$\min \quad \frac{1}{2}\|W^{ij}\|^2 + C\sum \xi_n^{ij}$$
$$\text{subjected to } \langle \phi(x).W^{ij}\rangle + b^{ij} \geq 1 - \xi_n^{ij}, \quad \text{if } y_n = i,$$
$$\langle \phi(x).W^{ij}\rangle + b^{ij} \geq -1 + \xi_n^{ij}, \quad \text{if } y_n = j,$$
$$\xi_n^{ij} \geq 0 \text{, for all n samples in class i and j} \tag{10}$$

As $f_{ij}(x) = -f_{ij}(x)$, we get total $k(k-1)/2$ varied decision functions for k-class classification problem. This method fits completely to the formerly known features of the SVM, so we can directly compute the borderlines between two distinct classes.

The "max wins" algorithm is the widely used algorithm for the identification of class in one-vs-one method. In this algorithm, as the name suggests, each classifier assigns one vote for its favoured class, and ultimately the final result is the class which have the maximum votes, i.e.

$$\text{the class of } x = \arg\max_i \sum_{j\neq i, j=1}^{k} \text{sign}(f_{ij}(x)) \tag{11}$$

where $\text{sign}(f_{ij}(x))$ is the sign function, i.e. it has the value 1 when f_{ij} is positive and 0 otherwise. Sometime more than one class have the same number of votes, in this situation tie condition arises. To overcome this problem each data in

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International Journal of Innovative Research in Computer and Communication Engineering

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the tie region, also known as unclassified region, is assigned to the nearby class using the real valued decision functions which can be given by:

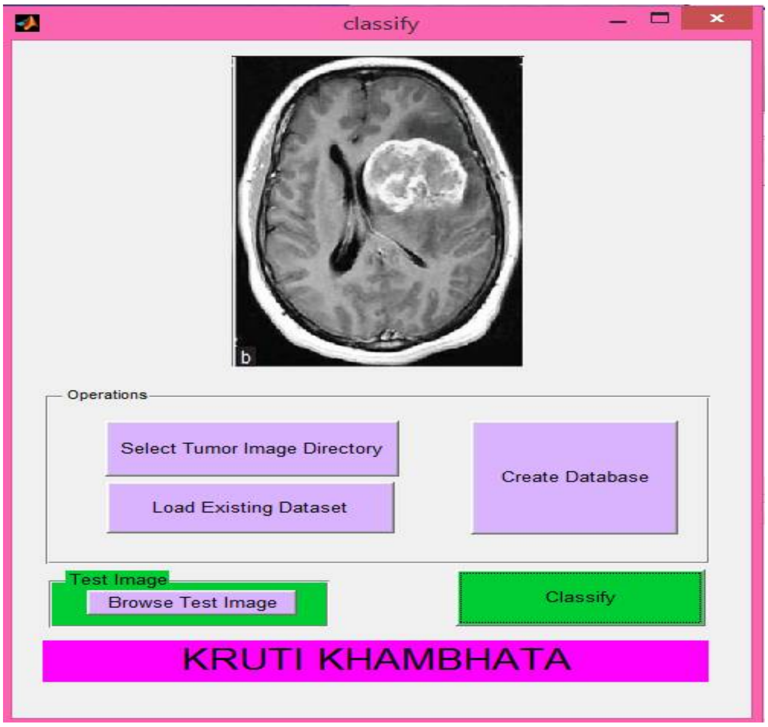
$$the\ class\ of\ x = \arg\ max_i \sum_{j \neq i, j=1}^{k} f_{ij}(x) \tag{12}$$

IV. Simulation Results

In this study five types of brain tumor classified based on the grade defined by the WHO. As per suggestion of doctor, The main features for classification of Tumor are Texture, Intensity and position of tumor. Considering these features Astrocytoma and Glioblastoma are classified by the intensity variations and enhancement of the region which can be given by Mean Amplitude (MA) and Mean Square Energy (MSE). Meningioma will originate at the periphery and Medulloblastoma lies in the center of the brain. Metastatic Melanoma has multiple tumor regions so the multiple intensity variations are there.

Classification of these five types of brain tumor is performed using Multiclass SVM. This SVM employs the one-versus-one approach for multiclass classification. The MATLAB simulation is carried out for all five types of classes using GUI.

The main features for classification of Tumor are Texture, Intensity and position of tumor. Considering these features Astrocytoma and Glioblastoma are classified by the intensity variations and enhancement of the region which can be given by Mean Amplitude (MA) and Mean Square Energy (MSE). Glioblastoma is intra-axial lesion and exhibits heterogeneous enhancement. Meningioma is extra-axial lesion and it exhibits homogeneous enhancement. Medulloblastoma is intraventrical lesion and exhibits heterogeneous enhancement. Metastatic Melanoma has multiple tumor regions so the multiple intensity variations are there. On the basis of these features five types of brain tumors are classified.



ISSN(Online): 2320-9801
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International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

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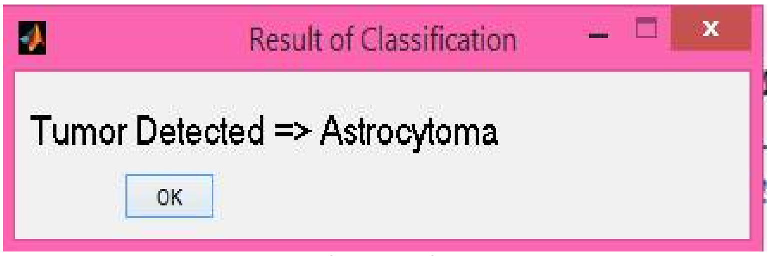

Fig. 7. Correct Classification of Astrocytoma Tumor

Here Fig. 7 represents the classification of test image into the /astrocytoma type. To check the different test images we have to load the dataset first which we have generated using available database and then we have to select test image then by pressing classify button we get the classification of test image into available classes.

Fig. 8 represent the classification of another test is shown in which Metastatic Melanoma tumor is detected.

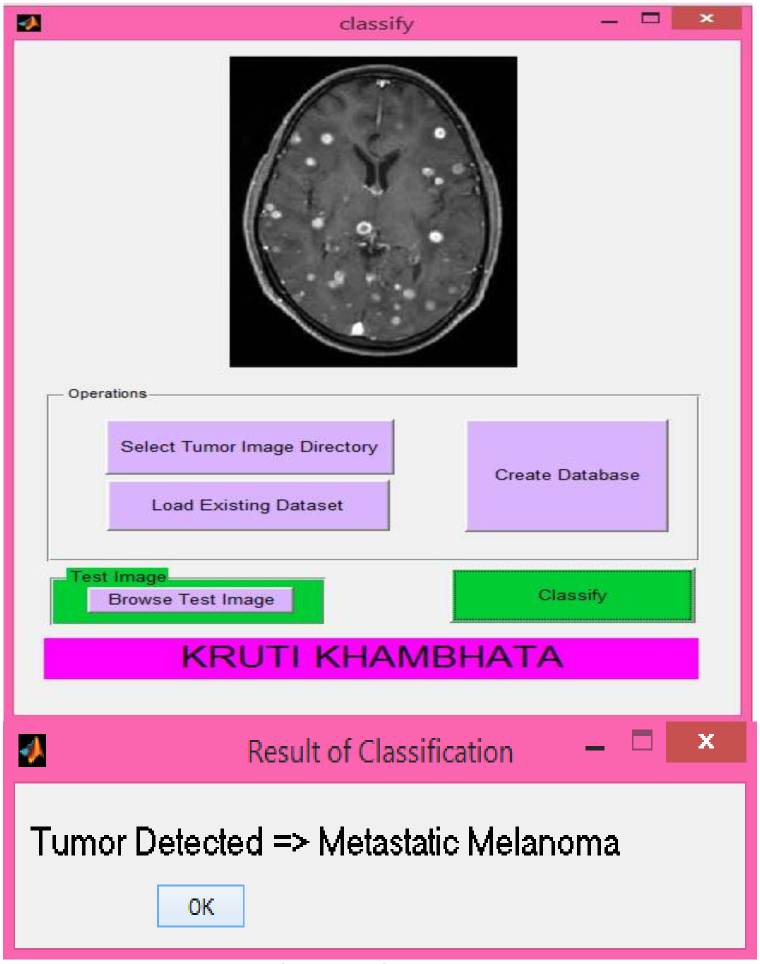

Fig. 8. Correct Classification of Metastatic Melanoma Tumor

Validation of any brain tumor segmentation method is must required due to its direct impact on surgical planning. Few years ago, due to lack of standard brain tumor database with ground truth data, researchers evaluate their proposed

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ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

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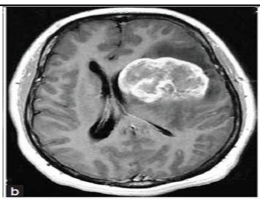
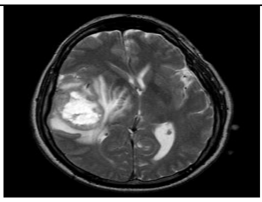
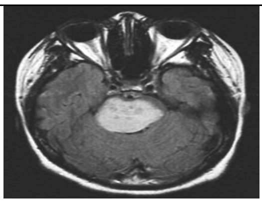
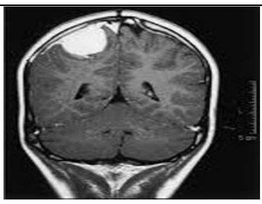
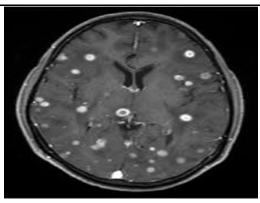
method on limited cases from their own data. Hence difficulty arises in comparing the performance of different methods. So, for quantitative performance evaluation several matrix are introduced which can be define as follow[6].

- True Positive (TP): Tumor region is correctly identified as tumor.
- True Negative (TN): Non tumor region is correctly identified as normal brain.
- False Positive (FP): Non tumor region incorrectly identified as Tumor.
- False Negative (FN): Tumor region incorrectly identified as normal brain.

The most common performance parameter used in medical image processing is accuracy which is given by,

$$\text{Accuracy} = \frac{(TP + TN)}{(TP + TN + FP + FN)} * 100 \tag{13}$$

Table 1: Results of Tumor classification for five different classes

Brain Tumor Image	Tumor Type	Accuracy
	Astrocytoma	76.14%
	Glioblastoma	76.65%
	Medulloblastoma	86.80%
	Meningioma	84.26%
	Metastatic Melanoma	82.23%

ISSN(Online): 2320-9801
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International Journal of Innovative Research in Computer and Communication Engineering

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Based on the features we have detected, we get the classification accuracy for each class which is shown in Table 1. We are getting 76.14% accuracy in Astrocytoma , 76.65% in Glioblastoma, 86.60% in Medulloblastoma, 84.26% in Meningioma and 82.23% in Metastatic Melanoma which is acceptable accuracy. The results is validated by the doctor.

V. Conclusion and Future Work

MRI is the standard technique to diagnose brain tumor which is widely used by doctors for manual segmentation. Computer aided analysis reduces the workload of doctor. Normally doctors do the biopsy for defining the specific type of tumor and its grade. Our proposed system is fully automatic which classifies the tumor in five different type of tumor based on the WHO grading system i.e Astrocytoma(Grade-I), Glioblastoma Multiforme(Grade-IV), Meningioma(Grade-II), Medulloblastoma (Child tumor) (Grade-IV) and metastatic melanoma(Grade-III). All the steps for automatic brain tumor extraction have been studied thoroughly and output of each step is obtained using MATLAB. Features of the tumor images are extracted using gabor , wavelet transform and colour moments which gives total 94 features. For multiclass classification one-against-one approach is employed with SVM which overcome the multiclass problem of traditional SVM. The result shows that it gives 76.14% accuracy in Astrocytoma , 76.65% in Glioblastoma, 86.60% in Medulloblastoma, 84.26% in Meningioma and 82.23% in Metastatic Melanoma which is acceptable accuracy.

In future, classification of low and high grade brain tumor can be done by extracting more features and by applying more accurate multiclass approach. We can also segment the various region in the tumor like edema that can affect the health of patients.

Acknowledgement

The authors would like to express sincere thanks to Dr. Sushil Mansingani (Consultant Radiologist, Baroda Imaging Center, Vadodara) for his guidance to understand medical terminologies regarding brain tumor and also for encouragement and support at every moment of the dissertation work. The paper uses the dataset available on the radiopaedia(http://radiopaedia.org/cases/) which is suggested by the doctor.

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ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 5, May 2016

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