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Astrocytoma Type of Brain Tumor Classification using Artificial Neural Network

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Abstract – **Brain tumor is a complex disease and its early detection and classification is very challenging. Astrocytoma is one of the commonest type of brain tumors. The detection and classification system of this type of tumor is based on magnetic resonance images (MRI). Brain tumors are classified into four grades (grade I – IV) according to world health organization (WHO) classification. The grade-I tumors are less malignant and grade-IV tumors are highly malignant. The classification based on only imaging findings is useful but occasionally equivocal in some cases which do not have typical characteristics of specific grade of tumor. In this work, image processing algorithm is developed to segment the tumor from the surrounding soft tissues and then classify the tumor into different grades. The work is carried out with MRI of different patients with astrocytoma type of brain tumors. The work involves two phases, namely learning/training phase and recognition/testing phase. In learning/training phase the artificial neural network (ANN) is trained for recognition of different astrocytoma types of brain tumor. The texture features are extracted from MRI whose tumor grades are known using gray level co-occurrence matrix (GLCM) and Gabor filters. These features are saved in knowledge base and are used to train the neural network. The brain MR images whose diagnosis is unknown are used for testing in recognition/testing phase. Tumor segmentation is achieved on these test images using watershed segmentation algorithm. The texture features in the detected tumor region are extracted. These features are compared with the stored features in the knowledge base. Finally a neural network classifier has been developed to recognize different grades of brain tumors.**

Keywords – **Brain Cancer, Brain Tumor Grades, MRI, Watershed Segmentation.**

I. Introduction

The brain is the center of the nervous system [1]. Physiologically, the function of the brain is to exert centralized control over the other organs of the body. The brain acts on the rest of the body both by generating patterns of muscle activity and by driving secretion of chemicals called hormones. This centralized control allows rapid and coordinated responses to changes in the environment. Healthy working of brain is crucial and very important for the human body.A brain tumor is defined as an abnormal growth of cells within the brain. Curing cancer has been a major goal of medical researchers for decades, but development of new treatments takes time and is not affordable. Early detection of brain tumor can save lives, when the brain tumors are benign and can be cured before they have a chance to grow or spread. Approximately 40 percent of all primary stage brain tumors are successfully treated with surgery and, in some cases, radiation. The number of malignant brain tumors appears to be increasing but for no clear reason. Brain tumor is a complex disease, classified into 120 different types [2]. So called nonmalignant (benign) brain tumors can be just as life-threatening as malignant tumors, as they squeeze out normal brain tissue, disrupt function and cause herniation. The glioma family of tumors comprises 44.4 % of all brain tumors. Glioblastoma type of astrocytoma is the most common and highly malignantglioma which comprises 51.9 %, followed by other types of astrocytoma at 21.6 % of all brain tumors. Brain tumors are the leading cause of cancer death in children under the age of 20. They are the second leading cause of cancer death among 20-29 year old males. Metastatic brain tumors result from cancer that spreads from other parts of the body into the brain. About 10-15% of people with cancer will eventually develop metastatic brain tumors. There are many types of brain tumors but among various types of brain tumors, the most prevalent and common is astrocytoma. Fig. 1 shows MRI of brain with tumor.

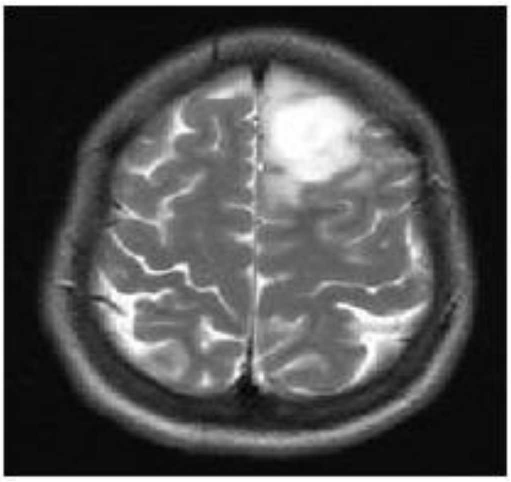


Fig.1. MRI of brain with tumor

II. Literature Survey

MRI is the most widely used modality for diagnosis of diseases of brain and related tissues of human body [3]. The multiplanar capability and excellent soft tissue resolution make MRI one of the best and hazard free modalities to image brain tumors. For brain tumor segmentation and classification, MRI is the most suitable and widely used imaging modality. Number of algorithms and classification techniques are developed for segmentation and diagnosis of brain tumor from MRI. The neural network based classification using MRI is a promising area. Most previous studies of neural network based MR image segmentation have employed the back propagation algorithm. M. Ozkan and B. M. Dawant presented a back propagation neural network approach for the automatic characterization of brain tissues from multimodal MR images. They studied the ability of a three layer neural network to perform segmentation based on a set of images acquired from a pathological human subject. Dipali M. Joshi, N. K. Rana and V. M. Misra [3] developed a brain cancer detection and classification system. A computer based procedure is developed to detect tumor blocks or lesions and classify the type of tumor using ANN in MRI images of different patients with astrocytoma type of brain tumors. AnamMustaqeem, Ali Javed and Tehseen Fatima [4] worked on brain tumor detection algorithm using watershed and thresholding based segmentation. It observed that in their work brain tumor detection helps in finding the exact size and location of tumor. Minakshi Sharma and SourabhMukharjee [5] worked on image segmentation technique for locating brain tumor. A. Suresh and K. L. Shunmuganathan [6] worked on a novel texture classification system based on GLCM. The texture classification is achieved by extracting the spatial relationship of pixel in the GLCM. Kailash D. Kharat, PradyumnaP.Kulkarni and M.B.Nagori [7] worked on two neural network techniques for the classification of the magnetic resonance human brain images. R. Mishra [8] has developed an MRI based brain tumor detection system using wavelet packet feature and artificial neural networks. The designed brain cancer detection and classification system uses watershed segmentation and found it most suitable to obtain a segmented image and uses conceptually simple classification method based on neural network. Texture features are used in training of the artificial neural network. The co-occurrence matrices at different directions are calculated and grey level co-occurrence matrix (GLCM) features are extracted. NitishZulpe and VrushsenPawar [9] worked on GLCM textural features for brain tumor classification. Amir EhsanLashkari [10] worked on neural network based method for brain abnormality detection in MR images using Gabor wavelets. This method uses neural network for classification. Snehal A. Kambale and V.S. Inamdar[11] worked on Gabor filter for feature extraction. Even though there are few classification techniques developed based on limited number of feature set, there is a necessity of classification method based on more features and improved accuracy.

III. Methodology

MR images are obtained from Siemens 1.5 Tesla MRI machine. T2 weighted images of matrix size 256x256 are selected for analysis. The data set consists of 30 subjects of astrocytoma, whose grades have been confirmed with radiologist. This data set is used for training of the software. Ten data sets of without diagnostic information are obtained during testing phase.

The system is developed in two phases namely learning/training phase and recognition/testing Phase. In learning/training phase the ANN is trained for recognition of different astrocytoma types of brain tumor. The known brain tumor MRI of different grades is used in the training database to train the neural network. Texture features are extracted using GLCM and Gabor wavelets. Features are represented as feature vectors and saved in memory. Feature extraction is done for all the images in training data and the ANN is trained with different parameters. The steps involved in tumor segmentation, feature extraction, neural network training and classification are shown in the Fig 2.

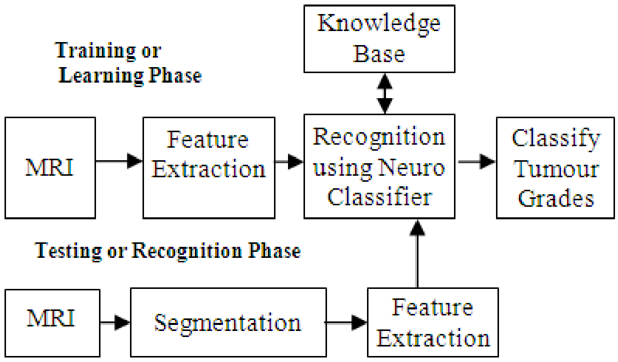


Fig.2. Processing steps of brain tumor segmentation, feature extraction and classification

The features extracted are saved in the knowledge bases which are used in successful classification of grades of test MR images. In recognition/testing phase the test image is read for classification. The region of interest is selected, then watershed segmentation is performed to segment the tumor affected region. Feature extraction is done for the tumor region and features are represented as feature vectors. These feature vectors are given as input to the classifier, where the test feature vectors are compared with the trained knowledge base vectors. The ANN classifier then classifies the image into different grades of astrocytoma type of brain tumor.

A. *Tumor Segmentation*

The first step in the system is to isolate the tumor region from the rest of the image. Division is done on the basis of similar attributes. Similarities are separated out into groups. Basic purpose of segmentation is the extraction of important features from the image, from which information can easily be perceived. Segmentation implies the division of an image into different connected regions that do not overlap[12]. The edema surrounding the tumors is mostly excluded and only the tumoral portion is used for analysis.

Watershed segmentation is one of the best methods to group pixels of an image on the basis of their intensities. Pixels falling under similar intensities are grouped together. Watershed is a mathematical morphological operating tool. Two basic principle methods for using watershed segmentation are

1. The computed local minima of the image gradient are chosen as a marker.
2. Merging is done as a second step. Watershed transformation using markers utilizes the specifically defined marker positions. These positions are either defined explicitly by a user or they can be determined by using morphological tools.

B. *Feature Extraction*

Features are the characteristics of the objects present in an image. Feature extraction is the procedure of extracting certain features from the pre-processed image. There are various techniques for measuring texture such as co-occurrence matrix, fractals, Gabor filters, wavelet transform. In this work GLCM features and Gabor filters are used for tumor classification.

GLCM: Gray-level co-occurrence matrix is the statistical method of examining the textures that considers the spatial relationship of the pixels. The GLCM functions characterize the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image, creating a GLCM, and then extracting statistical measures from this matrix.A GLCM is a matrix where the number of rows and columns is equal to the number of gray levels, G in the image. The matrix element *P* (*i*, *j* | ⇆*x*, ⇆*y*) is the relative frequency separated by a pixel distance (⇆*x*, ⇆*y*). Matrix element also represented as *P*(*i*, *j* | *d*,▼)which contains the second order probability values for changes between gray level *i*and*j* at distance *d* at a particular angle ▼ .

Angular Second Moment: It is a measure of homogeneity [9].

$$\mathrm{ASM} = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1}\{P(i,j)\}^2 \qquad (1)$$

Contrast: It calculates intensity contrast between pixels and its neighbor pixel for the whole image.

$$\mathrm{Contrast} = \sum_{n=0}^{G-1} n^2 \left\{\sum_{i=1}^{G}\sum_{j=1}^{G} P(i,j)\right\}, |i-j| = n \qquad (2)$$

Inverse Difference Moment

$$\mathrm{IDM} = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1}\frac{1}{1+(i-j)^2}P(i,j) \qquad (3)$$

IDM is also influenced by the homogeneity of the image. Because of the weighting factor $1 + (i - j)^2$IDM will get small contributions from inhomogeneous areas (i ≠ j). The result is a low IDM value for inhomogeneous images, and a relatively higher value for homogeneous images.

***Entropy*: It is a measure of randomness**

$$\mathrm{Entropy} = -\sum_{i=0}^{G-1}\sum_{j=0}^{G-1} P(i,j)\log\big(p(i,j)\big) \qquad (4)$$

Gabor features: In image processing, a Gabor filter is used as a linear filter for edge detection. Frequency and orientation representations of Gabor filters are similar to those of the human visual system, and they have been found to be particularly appropriate for texture representation and discrimination.

Gabor Filter: The two-dimensional (2D) Gabor filter decomposes an image into components corresponding to different scales and orientations [11] [13], thus capturing visual properties such as spatial localization, orientation selectivity, and spatial frequency. The 2D Gabor filter consists of a complex exponential centered at a given frequency and modulated by a Gaussian envelope. Because of the complex exponential, the filter has both real and imaginary parts. The general form of the real part is defined as follows:

$$G = \exp\left[-\frac{1}{2}\left(\left(\frac{x'}{\sigma_x}\right)^2 + \left(\frac{y'}{\sigma_y}\right)^2\right)\right] \times \cos(2\pi f x') \qquad (5)$$

$$x' = x\cos(\theta) + y\sin(\theta)$$

$$y' = y\cos(\theta) - x\sin(\theta)$$

Where σ_x and σ_y are the standard deviations of theGaussian envelope along the $x$and $y$axis. The parameters $f$and $\theta$are the central frequency and the rotation of the Gabor filter respectively.

C. Knowledge Base

Knowledge is any chunk of information that effectively discriminates one class type from another. In this case, tumor shows certain properties that other brain tissues will not and vice-versa. In the domain of MRI volumes, there are two primary sources of knowledge available. The first is pixel intensity in feature space, which describes tissue characteristics within the imaging system. The second is image/anatomical space and includes expected shapes and placements of certain tissues within the image, such as the fact that CSF (cerebral spinal fluid) lies within the ventricle. The nature of tumors limits the use of anatomical knowledge, since they can have any shape and occupy any area within the brain. As a result, knowledge contained in feature space is extracted and utilized.

D. Neural Network Classifier

A neural network classifier is used to detect candidate circumscribed tumor. ANN's are networks of inter connected computational units, usually called nodes [14] [15]. The input of a specific node is the weighted sum of the output of all the nodes to which it is connected. The output value of a node is, in general, a non-linear function (referred to as the activation function) of its input value. The multiplicative weighing factor between the input of node j and the output of node *i* is called the weight w_{ji}. An artificial neural network is an adaptive, most often nonlinear system that learns to perform a function (an input/output map) from data. Adaptive means that the system parameters are changed during operation, normally called the learning/training phase. After the training phase the artificial neural network parameters are fixed and the system is deployed to solve the problem in recognition/ testing phase. Back-propagation ANN's used in this study consist of one input layer, one or two hidden layers, and one output layer. With back-propagation, the input data (extracted features) is repeatedly presented to the artificial neural network, with each presentation the output of the neural network is compared to the desired output (grade of tumor) and an error is computed. This error is then fed back (back-propagated) to the artificial neural network and used to adjust the weights such that the error decreases with each iteration and the neural model gets closer and closer to producing the desired output. This process is known as training. The training of these networks consists in finding a mapping between a set of input values and a set of output values. This mapping is accomplished by adjusting the value of the weights w_{ji}, using a learning algorithm, the most popular of which is the generalized delta rule. After the weights are adjusted on the training set, their value is fixed and the ANN's are used to classify unknown input images.

IV. Results

The developed algorithm efficiently classifies the input MRI of brain cancer affected patients into a grade of astrocytoma type of tumor. The MRI of patients affected by brain cancer is used during recognition /testing phase. The features extracted from tumor region are compared with stored features in knowledge base. The developed system then classifies the image into a grade of the tumor for Astrocytoma type of brain cancer. The GLCM features obtained during feature extraction are listed below in Table 1.

Table 1: GLCM Features

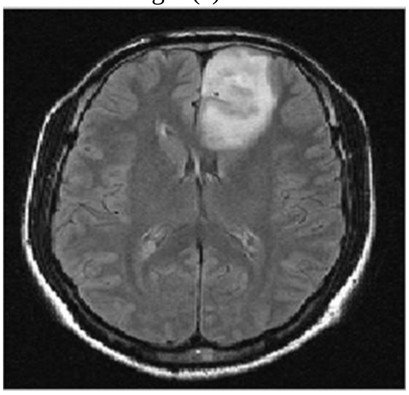
Grades	Contrast	ASM	Entropy	IDM
2	0.0141	6.4561	1.3455	1.2344
3	0.0149	7.9853	2.3224	1.3242
4	0.0048	2.5120	1.1455	1.3344

The GLCM were carried out with limited set of features with which classification results were less satisfactory. The additional features are extracted with Gabor features. The list of additional features that were extracted using Gabor filters is in total 66. Few of the Gabor features are listed in Table 2.

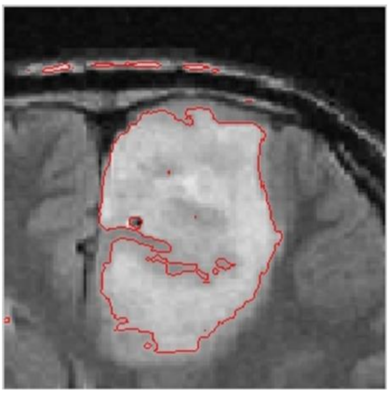
Table 2: Gabor Features

Grades	Feature1	Feature2	Feature3	Feature4	Feature5
2	0.4043	0.3931	0.3594	0.2986	0.2101
3	0.5205	0.5064	0.4598	0.3779	0.2565
4	-2.0226	-2.1830	-1.8890	-1.6307	-1.4952

The test image from testing database for segmentation and classification is shown in Fig. 3(a). Segmentation is performed on test image with 500 iterations and shown Fig 3(b). Segmented tumor region ready to perform feature extraction is shown in Fig. 3(c).



(a)



(b)

(c)

Fig.3. (a) Input MRI (b) Watershed segmentation to detect tumor region (c) Segmented tumor after 500 iterations

Table 3 shows the original grade of astrocytoma type of tumor diagnosed by the doctor and result of classification using the developed system for the same image. Considering the above table the system accuracy and performance can be approximated to 99.02%.

Table 3 Classification of Tumor

Test Image	Diagnosed Grade	Classified Grade
Case1	2	2
Case2	3	3
Case3	3	3
Case4	3	3
Case5	4	4
Case6	4	4

It is observed that the system works efficiently for detection and classification of brain cancer. Results of classification of unknown brain cancer images are matching with the diagnosis results of experts.

IV. Conclusion

Most of the methods available can only detect location and size of the tumor and can provide information about the type of tumor. In some equivocal cases, isolated imaging finding based classification is erroneous. Many tumor forms can only be diagnosed after a sample of suspicious tissue has been removed and tested (biopsies). Brain biopsy is invasive, not widely available, and very expensive and may lead to neurological deficits due to procedure itself. The system developed in this study classifies and identifies pathological tissues in a non invasive and automated fashion. Brain tumor detection and classification system is implemented using ANN. The design based on image processing techniques, artificial neural network and graphical user interface is successfully completed and used in the system to detect and classify the tumor. The designed brain tumor detection and classification system uses conceptually simple classification method using the neural network. Textures features are used in the training of the ANN. Co occurrence matrices at different directions are calculated and GLCM features and Gabor features are extracted from the matrices. The above procedure effectively classifies the tumor types in brain images taken under different clinical circumstances and technical conditions, which were able to show high deviations that clearly indicated as abnormalities in areas with brain disease. This system provides precision in the detection and classification of astrocytoma type of brain tumors. The system has been tested only with the limited sample images. The test input image of grade 1 was not available in the training set. It is essential to use large number of patient's data which will improve the accuracy of the system.

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