IJISET - International Journal of Innovative Science, Engineering & Technology, Vol. 1 Issue 6, August 2014.
www.ijiset.com
ISSN 2348 – 7968

Brain Tumor Classification Based on Statical Feature Extraction

Shrikant Burje[1] and Sourabh Rungta[2]

[1] Research Scholar, CSVTU, Bhilai, Chhattisgarh, India

[2]Professor, RCET Bhilai, Chhattisgarh, India

Abstract

In this paper, Automated brain tumor classification is implemented by employing Probabilistic Neural Network with image and data processing techniques. Human inspection being the conventional method for medical resonance brain images classification and tumors detection. Operator-assisted classification methods are impractical for larger amount of data and are also non-reproducible. Medical Resonance images normally contains a noise which is caused by operator performance that can lead to serious inaccuracies classification. For Neural networks the use of artificial intelligent techniques, for instance, has shown great potential. Hence, Probabilistic Neural Network is applied for this purpose in this paper. Decision making has been performed in two stages: feature extraction, Neural Network training. Probabilistic Neural Network gives fast and accurate classification and is a promising tool for classification of the tumors.

Keywords:*Brain Tumor, Image Segmentation, Feature Extraction.*

1. Introduction

Brain Tumors: Brain tumors are abnormal masses in or on the brain. Tumor growth may appear either as a result of uncontrolled cell proliferation, or may be a failure of the normal pattern of cell death, or both [46]. Brain tumors can be either primary or secondary.

Primary tumorsare composed of cells just like those that belong to the organ or tissue where they start. A primary brain tumor basically starts from cells in the brain. Mostly the brain tumors in the children's are primary, and at least half of all primary tumors originate from cells of the brain that support the body's nervous system. Tumors that are related to the nervous system are calledgliomas, and they originate in the brain's glia cells. Central nervous system tumors constitute a heterogeneous group of diseases that vary from benign, slow-growing lesion to aggressive malignancies that can cause death within a few months if left untreated. Each of these tumors has unique clinical, radiographic, and biological characteristics that normally dictates. Benign tumors grow slowly and do not spread to that extent. However, benign tumors can be very serious and may be life threatening; growing in a limited confined space, a benign tumor can even put pressure on the brain and compromise its functionality. Malignant tumors grow comparatively quickly and can spread to surrounding tissues. "Malignancy" or "malignant" almost always refers to cancer. In general, the glial neoplasms that are seen commonly in adults include low-grade tumors such as the infiltrating astrocyoma, oligodendroglioma, and mixed low-grade tumors. Intermediate-grade tumors include anaplastic astrocytoma or anaplastic oligodendroglioma, or mixed anaplastic tumors. The most malignant glial neoplasm beingglioblastomamultiforme.Many other tumors exist such as meningioma and ependymoma. Brain tumors of childhood normally include pilocytic astrocytoma, primitive neuroectodermal tumors such as medulloblastoma, ependymoma, and a variety of rare tumor types such as the germ cell tumors and atypical rhabdoid tumors of the central nervous systems [3]. The malignancy of brain tumor is not only dependent on the pathological malignancy, but also on the location, growth pattern and rate of its growth. An otherwise benign tumor maybe situated in an area of brain that contain vital centers and thus may cause great harm, rather than a highly malignant tumor in an area that may be involved in abstract functions and may not cause symptoms for a long time. The location of the tumor is extremely important in the diagnosis as well. MRI alone cannot reliably differentiate between the different types of tumors on imaging, however combining the information with location can be very helpful in predicting the exact histology of the tumors.

Secondary tumorsare made up of cells from another parts of the body that spreads to one or more of the neighboring areas. Actually Secondary brain are made up of cells from another parts of the body that spreads to one or more of the neighboring areas. Actually Secondary brain tumors are composed of cancer cells from somewhere else in the body that have metastasized, or spread, to the brain, such as osteosarcoma (a primary bone tumor) or rhabdomyosarcoma (a primary tumor of muscle). These lesions tend to be rather well defined and may be more easily removed by surgery [6].

Brain tumors are relatively common tumors, especially in children. A tumor is any mass that occupies space. It is also known as space-occupying lesion (SOL). Not all tumors are cancer, and not all cancers are tumors.

With different criteria, brain tumors can be classified as:

1. Location in the skull:

a. Intra-axial (inside the brain)

ISSN 2348 – 7968

b. Extra-axial (outside the brain but inside the skull)
2. Location in brain:
a. Cerebral
b. Cerebellar
c. Brainstem
d. Convexity tumors
3. Location in compartments:
a. Supratentorial (above the tentorium cerebelli)
b. Infratentorial
c. Anterior fossa
d. Middle fossa
e. Posterior fossa
f. Orbital
g. Cerebellopontine (CP) angle
4. Origin of tumor
a. Glial cells
b. Neurons
c. Meninges
d. Germ cells
5. Pathology
a. Benign
b. Malignant

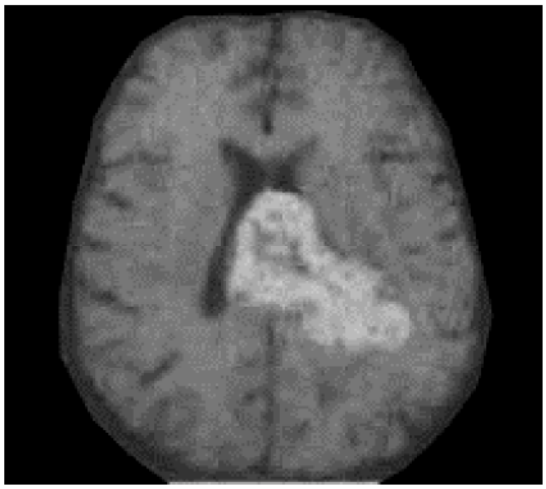
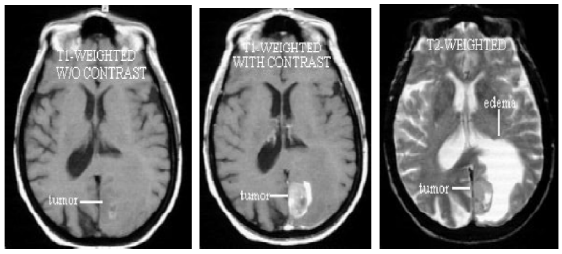


Fig. 1 Brain image with a tumor.

MR Image Characteristics of Brain Tumors:MRI has become firmly established as the premier diagnostic modality for the head [4]. It is most commonly utilized for lesion detection, defining the extent, detection of spread and in evaluation of various residual or recurrent disease. (Vezina[51]) MR – with its multi-planar imaging capabilities, higher end sensitivity to pathologic processes, and excellent anatomic detail – will always be the choice of imaging study in the evaluation of intracerebral tumors if cost and availability were not issues [7]. MRI has better sensitivity for brain tumors compared to CT, both in terms of detection as well as in showing explicitly the extent of the tumor. The major aspect of multi-planar imaging is itssuperior tumor localization, than just increasing the detection rate of lesions. MRI provides significantly more information about intrinsic tissue characterization and parallels findings on gross pathology. The effects of necrosis on MRI are complex and varied but can often be identified with near-certainty. The association of cysts with certain neoplasms has long been utilized as an aid to differential diagnosis by neuroradiologists and MRI is very good at picking up cysts that are very sharply demarcated, round or ovoid masses. MRI uniquely exhibit hemorrhage, because of the paramagnetic properties of many of the blood-breakdown products. The signal intensity pattern of intratumoral hemorrhage differs from benign intracranial hematomas. Fat-containing neoplasms (e.g., teratoma, dermoid, lipoma) are easily identified or detected on MRI. The dilated and increased blood vessels to the tumors may also be seen well on MRI and magnetic resonance angiography (MRA).

Both T1- and T2-weighted images are useful to brain imaging. Cerebrospinal fluid (CSF) has very long T1 and T2 relaxation time and therefore appears dark on T1-weighted images and very bright on T2-weighted images. As the fluid becomes more saturated with proteins content, the T1 and T2 time decreasesgradually and the signal strength drops there by leading to darker contrast effect. This helps in clear diffrentiation between pure fluids and those with more proteinaceous matter in them (e.g. the difference between a fluid filled cyst and a more heterogeneous tumor). Additionally, T1-weighted images exhibits change in tissue homogeneity in the brain such as tumors and/or dead tissue. T2-weighted images are more helpful in diagnosis since most pathologic activity in the brain leads to an increase in fluid content (vasogenic or cytotoxicedema). The development of tumors in the brain can be diagnosed with both CT and MRI scans, but only MRI has the resolution to detect heterogeneity within tumors that might indicate its origin and can be helpful in its treatment. Tumors can easily be differentiated from cysts, which are commonly fluid filled and not supplied with blood. Tumors are vascularized which allows them to grow faster and resist to the treatment. Intravenous contrasting agents can help to determine the amount of vascularization and define the growth's size and even its shape. Glioblastomas, the brain tumors made of glial tissue, make up more than 50% of all brain tumors. The images below, shows T1-weighted images before and after contrast agent injection, and T2-weighted image shows a large corresponding gliobalstoma that has developed in the left occipital lobe of this patient.

ISSN 2348 – 7968



(a) T1-weighted (b) T1-Contrast Enhanced (c) T2-Weighted

Fig 2 Appearance of tumor in T1-weighted, T1-contrast enhanced and T2-weighted images of the same axial slice

2. Previous Work

Clustering Method: Unsupervised techniques, also called "clustering", need no human intervention and can automatically find the structures in the data. Clustering methods include k-nearest neighborhood (kNN), k-means, fuzzy c-means (FCM), and self-organizing map networks. Velthuizenet al. (1995[9]) proposed a refinement of FCM segmentation by allowing the small classes like tumors to have a noticeable effect on a validity measure, called validity guided clustering, and a genetic algorithm to improve classification from FCM (1996[5]) to segment tumor in 2D. Three data sets (one glioblastoma, one meningioma and one astrocytoma) were tested. The detection rate of meningioma is 76%, gioblastoma 81%, and astrocytoma only 17%. Ahmed et al. (2002[1]) proposed a bias-corrected FCM algorithm (BCFCM) modified by neighborhood field effect. The algorithm was used to compensate for the in homogeneity caused by imperfections in the radio-frequency coils or the problems associated with the acquisition sequences, and allow the labeling of a pixel (voxel) tobe influenced by labels in its immediate neighborhood. In noisy images, the BCFCM technique produced better results than Expectation-Maximization (EM) algorithm. However, it is limited to single-feature inputs, and the algorithm needs further clinical evaluation.

Knowledge-based Method: Knowledge-based techniques combine knowledge of anatomy, signal intensity or spatial location of anatomic structures with unsupervised methods. Thompson (Thompson et al, 1998[45]) and Li (Li et al, 1993[27]) suggested aKnowledge-based approach that estimates symmetry of CSF. A tumor can thus be detected only on slices that disturb the CSF spatial symmetry. The measures used were based strictly on predefined intensity thresholds that can vary from one data set to another. Presumingthe tumors appear to have intensity, higher than that of GM on T2-weighted images. Moreover it was applied to 2D images, the symmetry characteristics of CSF will be influenced, when the collectedaxial slice is not perpendicular to the MSP. Clark et al. (1998[10]) proposed a multispectral analysis tool that segments and labels glioblastoma-multiforme tumor, and compared with kNN. Yoon et al. (1999[55]) used FCM for the initial binary classification of brain, one class is WM and GM, another class is CSF. A symmetry property measures based on the number of pixels, moment invariants and Fourier descriptors were defined to quantify the normality of slices. The related weights for these three parameters were set without any proof and the quantification of normality was performed only on 40 slices in 1 normal and 2 abnormal T2-weighted studies. Lynn et al. (2000[31]) introduced an automatic segmentation of non-enhancing brain tumors based on FCM initial segmentation and image processing techniques controlled by domain knowledge system. Using signal intensity and spatial location of anatomic structures derived from a digital atlas, Michael et al. (2001[10]) proposed an automatic algorithm for tumor segmentation using iterative statistical classification and region growing, which takes 5-10 minutes. Structural and radiometric asymmetry was analyzed through a large deformation image warping in 2D (Joshi et al., 2003[22]). Nine tumors and four normal cases were tested. There is no information on the running time. The second stage of algorithm was based on Christensen's warping algorithm (Christensen et al., 1996[12]) that is extremely time consuming Christensen, 1994[11]).

Model-based Method: Model-based techniques and deformable models have also been used in tumor detection and segmentation. Capelle et al. (2000[6]) proposed Markov random field model-based unsupervised segmentation in combination with anisotropic filtering and a posterior estimator to segment the brain into homogenous regions to localize possible tumors. Moon et al. (2002[13]) described a model derived from the digital brain atlas containing the spatially varying prior probability maps for the location of WM, GM, CSF, brain tumors and edema. Based on the model, the expectation maximum algorithm is used to remodify the model with individual subject's information about tumor location, and to segment the tumor and edema. Ho et al (2002[19]) proposed an iterative level-set evolution with a region competition segmentation method with an initialization probability map obtained from intensity-based fuzzy classification.

Edward et al. (2003[16]) proposed a semi-automated quantification of MS lesions using a geometrically constrained region growth and directed multispectral segmentation, in which the initial "seed" is set manually. The operation times of these two methods being 3 and 10 minutes, respectively.

ISSN 2348 – 7968

3. Proposed Approach

Basically, two main phases are employed in this project which is theoretical phase and practical phase. Theoretical phase involves the process of reading and understanding, reviewing of theories, studying and surveying, classification and detection techniques on medical image fields. There are 4 stages involved in the proposed model which starts from the data input to output. The first stage being the image processing system. Mainly in image processing system, image acquisition and enhancement are steps that need to be done. In this project, these two steps are skipped and all the images are collected from available resources. The proposed model requires converting the image into a format capable of being manipulated by the computer. The MR images are basically converted into matrices form by using MATLAB. The proposed approach mainly contains four steps. This convention makes working with images in MATLAB similar to working with any other type of matrix data, and makes use of the full power of MATLAB available for image processing applications. An intensity image is a data.

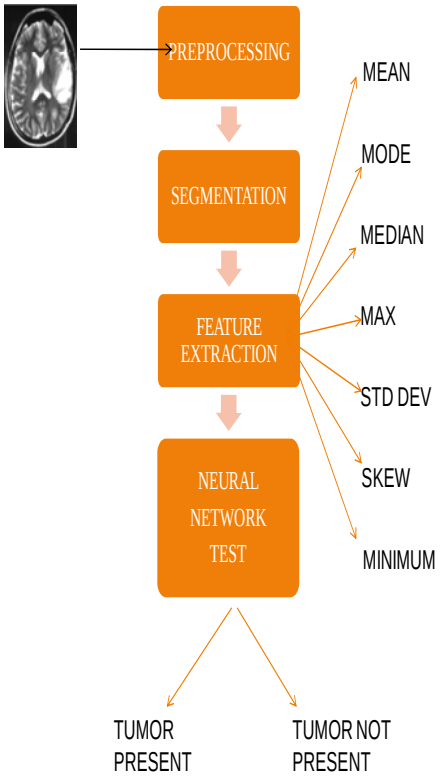


Fig 3

Feature extraction involves simplifying the amount of resources required to describe a large set of data precisely. The number of variables involved is one of the major problemwhen performing analysis of complex data. Analysis when done with a numerous variables generally involves a large amount of memory and/or computation power or a classification algorithm that over fits the training sample and generalizes inadequately to new samples. Feature extraction being a general term for methods of constructing combinations of the variables to get around these problems while still describing the data with sufficient accuracy. Best results are normally achieved when an expert constructs a set of application-dependent features.

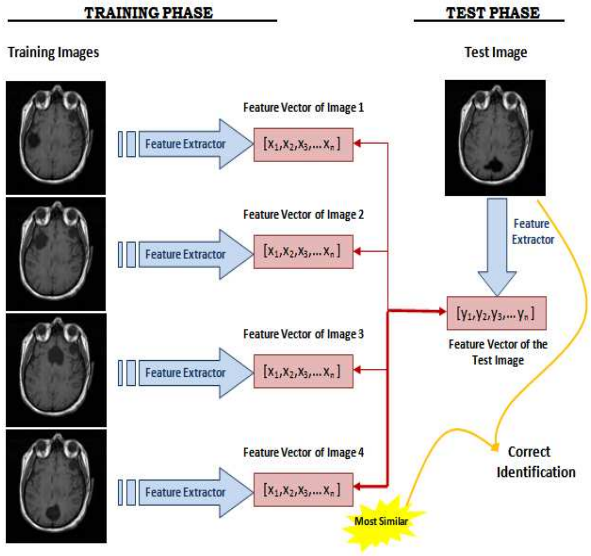


Fig 4

4. Result

Table 1 Classification of patientsand brain MRI studies performed

	Mean	StdDev	median	Mode	Min	Max
1	195.13	52.227	216	239	32	255
2	199.594	45.032	234	252	49	255
3	182.336	53.799	215	255	18	255
4	199.931	48.936	237	255	13	255
5	199.377	43.431	222	255	13	255
6	155.42	68.351	216	255	12	255
7	153.504	68.517	256	255	12	255
8	159.171	54.736	289	255	20	255
9	155.781	62.51	234	255	12	255
10	157.355	67.877	231	255	12	255
11	145.304	57.277	265	255	13	255
12	197.183	82.313	253	255	13	255
13	156.497	62.554	199	255	12	255

ISSN 2348 – 7968

14	176.616	71.43	198	255	12	255
15	163.779	66.179	196	255	12	255
16	80832	148.747	53.561	255	3	255
17	47428	173.656	57.982	255	5	255
18	184730	199.917	37.096	221	14	255
19	22852	171.825	62.238	255	47	255
20	22138	173.377	64.728	255	32	255
21	29844	204.069	43.011	255	11	255
22	49836	196.743	44.748	236	7	255
23	72824	197.524	61.482	246	32	255
24	26500	203.108	44.34	239	23	255
25	70304	197.119	62.088	245	32	255
26	148.747	53.561	195	255	13	255
27	173.656	57.982	194	255	15	255
28	199.917	37.096	193	221	14	255
29	171.825	62.238	193	255	47	255
30	173.377	64.728	234	255	32	255
31	205.069	43.011	193	255	11	255
32	206.743	44.748	253	236	7	255
33	207.524	61.482	265	246	9	255
34	203.108	44.34	189	239	9	255
35	207.119	62.088	199	245	2	255
36	205.13	52.227	234	239	2	255
37	203.594	45.032	198	252	2	255
38	202.336	53.799	196	255	3	255
39	201.931	48.936	194	255	3	255
40	204.377	43.431	193	255	2	255

Table 2 Classification of patientsand brain MRI Test tumor

Mean	Median	StdDev	Mode	Min	Max
223.008	180	41.85	255	19	255
238.215	229	61.33	246	30	255
214.322	172	54.787	255	8	255
219.849	230	47.593	231	20	255
202.189	171	54.594	255	9	255

Table 3 Classification of patientsand brain MRI Test Non-tumor

Mean	StdDev	Mode	Min	Max	Median
175.597	16.014	165	136	251	173
204.386	9.614	201	144	255	203
193.553	13.535	183	171	252	189
193.617	13.598	184	171	254	189
194.109	13.792	184	173	255	190

5. Conclusion

Here the output will be in the form of 1 and 0. For nontumor images the output will be 0 and for tumor image output will be 1. We can see the output in the output data of network data manager. In the testing data I have used 5 tumor image and 5 non tumor image .Hence the output data gives the output in 5 column form.

The proposed algorithm shows an effective method for detection of the brain tumors in the 2 dimensional MRI in the various types of image formats like jpeg, bmp formats. This method is much faster than other existing method for detection of tumor. Accuracy of result is depends on the selection of input image having boundary of tumor region and also size of the tumors which have got grown in the tissues.

References

[1] M. Celenk, “A Color Clustering Technique for Image Segmentation,” Computer vision, Graphics and Image Processing, vol. 52, pp. 145-170, 1990.
[2] Y. I. Ohta, T. Kanade, and T. Sakai, “Color Information for Region Segmentation,” Computer Graphics and Image Processing, vol. 13, pp. 222-241, 1980.
[3] S. E. Umbaugh, “Computer vision in medicine: Color metrics and image segmentation methods for skin cancer diagnosis,” Ph.D. dissertation, Dept. of Electrical Engineering, University of Missouri-Rolla, MO,1990.
[4] F. Ercal, A. Chawla, W. V. Stoecker, and R. H. Moss, “Diagnosing Malignant Melonoma Using a Neural Network,” Intelligent Engineering Systems Through Arrificial Neural Networks, vol. 2, ASME Press, pp.
[5] J. E. Golston, R. H. Moss, and W. V. Stoecker, “Boundary Detection in Skin Tumor Images: An Overall Approach and A Radial Search Algorithm,” Pattern Recognition, vol. 23, no. 11, pp. 1235-1247, 1990.
[6] P. A. Dhawan and A. Sicsu, “Segmentation of images of skin lesions using color and texture information of surface pigmentation,” Computerized Medical Imaging and Graphics, vol. 16, pp. 163-177, May 1992.
[7] S. E. Umbaugh, R. H. Moss, and W. V. Stoecker, “An automatic color segmentation algorithm with application to identification of skin tumor borders,” Computerized Medical Imaging and Graphics, vol. 16, pp.227-235, May 1992.
[8] A. Rosenfeld and A. C. Kak, Digital Picture Processing, 2nd ed., vol. I. Orlando, FL: Academic Press, 1982, pp. 261-264. Richard 0. Duda and Peter E. Hart, Pattern Classijication and Scene Analysis New York Wiley, 1973, pp. 290-292.
[9] J. E. Golston, W. V. Stoecker, R. H. Moss, and I. P. S. Dhillon,“Automatic detection of irregular borders in melanoma and other skin tumors,” Computerized Medical Imaging and Graphics, vol. 16, pp.199-203, May 1992.

ISSN 2348 – 7968

[10] Ahmed M.N., Yamany S.M., Mohamed N., Farag A.A., Moriarty T., "A modified fuzzy c-means algorithm for bias field estimation and segmentation of MRI data". IEEE Trans Medical Imaging, 21(3), 193-199, 2002.
[11] Christensen G.E., "Deformable shape models for anatomy". Electrical Engineering D.Sc. Dissertation, Washington University, St. Louis, Missouri, 1994.
[12] Christensen G.E., Rabbit R.D., Miller M.I., "Deformable Templates Using Large Deformation Kinematics". IEEE Trans Medical Imaging, 5(10), 1435-1447, 1996.
[13]Cocosco C.A., Kollokian V., Kwan R.K.S., Evans A.C., "BrainWeb: Online Interface to a 3D MRI Simulated Brain Databas. NeuroImage".3rd International Conference on Functional Mapping of the Human Brain HBM 97, Copenhagen, 4(2-4), S425 – Proc. 1997.
[14]David G. S., Richard O. D., Peter E. H., Pattern Recognition.
[15]Denoeux T., "A k-nearest neighbor classification rule based on Dempster-Shafer Theory". IEEE Trans. Systems Man Cybernet.25 (5), 804-813, 1995.
[16] Edward A.A., Chihiro T., Michel J.B., Andrew G., Saara T., Sven E., "Accuracy and reproducibility of manual and semiautomated quantification of MS lesions by MRI". Journal of Magnetic Resonance Imaging, 17(3), 300-308, 2003.
[17] AnantBhardwaj,Kapil Kumar Siddhu," An Approachto Medical Image Classification Using Neuro Fuzzy Logicand ANFIS Classifier, International Journal of Computer Trends and Technology –volume 4 Issue 3-2013.

ShrikantBurjehas received degrees B.E (Electronics and Tele) and M.E. (Electronics) from Amravati University,Maharashtra State, India in 1997 and 2003 respectively. He is presently working as Assistant Professor in the Department of Electronics, RCET Bhilai Chhattisgarh State, India. He is a member of professional bodies like Indian society of technical Education and Institution of Engineers. His research interests include Medical Image processing and soft computing techniques.

Dr. SourabhRungta received his M. Tech. (Computer Technology) degree in 2002 from NIT Raipur, (India). Presently he is working as Professor at RCET Bhilai, (India). He received his Ph.D. degree in Computer Science Engineering in 2014 at CSVTU (India). He ismember of various professional bodies like IE, ISTE, IEEE and Fellow of IETE.