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Brain Tumor Detection and its Severity Analysis using Texture Features and Artificial Neural Network

G. Venkateswara Rao[1]
Associate Professor
Department of CSE,
St.Mary's Group of Institutions Guntur
Chebrolu(V&M),Guntur(Dt),
Andhra Pradesh – India

O. Koteswara Rao[2]
Associate Professor
Department of CSE,
St.Mary's Group of Institutions Guntur
Chebrolu(V&M),Guntur(Dt),
Andhra Pradesh – India

Abstract: Medical image processing is one of the most challenging and emerging field. Processing MRI images is one of the most important parts to diagnose brain tumour. The quantitative analysis of brain tumour allows obtaining useful key indicators of disease progression. This paper presents an approach in computer-aided diagnosis for early prediction of brain tumour using texture features and neural network classification. This paper describes the proposed strategy for detection; extraction and classification of brain tumour from MRI images of brain. This incorporates segmentation and morphological functions; which are the basic functions of image processing. This process includes tumour segmentation, tumour detection and severity analysis. Severity of the tumour is analysed using artificial neural network by classifying them into various classes of brain tumour.

Keywords: MRI image, Brain Tumour, Texture Features, Artificial Neural Network, Severity Analysis.

I. INTRODUCTION

Brain is the center of thoughts, emotions, memory and speech. It also control muscle movements and interpretation of sensory information (sight, sound, touch, taste, pain etc.) [1]. Brain tumour is a localized intracranial lesion which occupies space with the skull and tends to cause a rise in intracranial pressure. Tumours can affect any part of the brain and depending on what part(s) of the brain it affects can have a number of symptoms like seizures, difficulty with language, mood changes, change of personality, and changes in vision, hearing and sensation, difficulty with muscle movement, difficulty with coordination control etc. [3]. Brain tumour can be counted among the most deadly and intractable diseases. Tumours may be embedded in regions of the brain that are critical to manage the body's vital functions, while they shed cells to invade other parts of the brain, forming more tumours too small to detect using conventional imaging techniques[4]. In recent years, the occurrence of brain tumours has been rising. Unfortunately, many of these tumours are detected in later stage, i.e. mostly after symptoms appear. It is much easier and safer to remove a small tumour than a large one [5]. Computer-assisted surgical planning and advanced image-guided technology have become increasingly used in Neuro surgery [2]. Tumour is defined as the abnormal growth of the tissues. Brain tumor is an abnormal mass of tissue in which cells grow and multiply uncontrollably, seemingly unchecked by the mechanisms that control normal cells [6]. Brain tumours are of two main types which are benign and malignant.

A. *Benign Tumours*

Benign brain tumours do not contain cancer cells usually, benign tumours can be removed, and they seldom grow back. The border or edge of a benign brain tumour can be clearly seen. Cells from benign tumours do not invade tissues around them or spread to other parts of the body [7]. However, benign tumours can press on sensitive areas of the brain and cause serious health problems. Unlike benign tumours in most other parts of the body, benign brain tumours are sometimes life threatening. Very rarely, a benign brain tumour may become malignant [9].

B. *Malignant Tumour*

Malignant brain tumours are generally more serious and often is life threatening. It may be primary (the tumour originate from the brain tissue) or secondary (metastasis from others tumour elsewhere in the body) [10].They are likely to grow rapidly and invade the surrounding healthy brain tissue. Very rarely, cancer cells may break away from a malignant brain tumour and spread to other parts of the brain, to the spinal cord, or even to other parts of the body [11].

C. *Classification of Tumours*

Brain tumours are basically classified on bases of tissue of origin, location, primary or secondary (metastatic) and grading [12]. Basically tumours are classified into

- Gliomas
  I. Astrocytoma (Grades I & II)
  II. Anaplastic Astrocytoma
  III. Glioblastoma Multiforme
- Oligodendroglioma
- Ependymomas
- Medulloblastoma
- CNS Lymphoma

In this paper, the classification of Gliomas tumours are subdivided into 3 types like class 1, class 2, and class 3.

Class 1: Astrocytoma is slow growing, rarely spreads to other parts of the CNS, borders not well defined.

Class 2: Anaplastic Astrocytoma will grow faster.

Class 3: Glioblastoma Multiforme (GBM) most invasive type of tumour, commonly spreads to nearby tissue, grows rapidly.

The brain tumours are diagnosed using various methods like Computed Tomography (CT) scans, Diffusion Tensor Imaging (DTI) scans, Magnetic Resonance Imaging (MRI) scans, Positron Emission Tomography (PET) scans, and Biopsy (tissue sample analysis). The most best preferred method for this project is MRI.

II. LITERATURE SURVEY

The various tumor detection approaches are classified into 4 categories. They are as follows: 1) thresholding approach, 2) region growing approach, 3) Genetic Algorithm approach and 4) Neural network approach. Several authors suggested various algorithms for segmentation. The threshold technique is by making decision based on the local raw pixel information and edge based method is centered on contour. Thresholding and edge detection being one of the most important aspects of image segmentation, it comes prior to feature extraction and image recognition system for analyzing images. It helps in extracting the basic shape of an image, overlooking the minute unnecessary details [17]. Manoj et. al., proposed a method based on histogram thresholding [18]. They follow a concept that after dividing the image into two equal halves, histograms are compared to detect the tumor and cropping method is used to find an appropriate physical dimension of brain tumor. In the region based technique, the images are partitioned by organizing the nearest pixel of similar kind. The region-based techniques with an assumption that adjacent pixels in the same region have similar visual features such as grey level, color value, or texture. Split and merge approaches were used and its performance largely depends on the selected homogeneity criterion [19]. Instead of tuning homogeneity parameters, the seeded region growing (SRG) technique is controlled by a number of initial seeds. If the numbers of regions were approximately known and used to estimate the corresponding parameters of an edge detection process. It is possible to combine region growing and edge detection for image segmentation. The important process in the automated system is brain image classification.

The main objective of this step is to differentiate the different abnormal brain images based on the optimal feature set. Though this approach claimed a faster convergence rate, it may not be much useful because of its low accuracy than Artificial Intelligent (AI) techniques. A hybrid approach for classification of brain tissues in MRI based on genetic algorithm [20]. The optimal texture features are extracted from normal and tumor regions by using spatial gray level dependence method. It is concluded that, Gabor filters are poor due to their lack of orthogonally that results in redundant features at different scales or channels. Wavelet Transform is capable of representing textures at the most suitable scale, by varying the spatial resolution and there is also a wide range of choices for the wavelet function. Application of various artificial neural networks for image classification is analyzed by classifying MRI brain images into normal and brain tumor in particular, is a crucial task. A wavelet and co-occurrence matrix method based texture feature extraction and Probabilistic Neural Network for classification has been used as new method of brain tumor classification [16].

III. PROPOSED METHODOLOGY

The work carried out involves processing of MRI images of brain tumour affected patients for detection and classification on different types of brain tumours. The image processing techniques like histogram equalization, image segmentation, image enhancement and then extracting the features of detection for tumour. Extracted feature are stored in the knowledge base and a suitable neural network classifier is developed to recognize the different types of brain tumours. The steps involved in detecting the brain tumour and classifying according to its severity is described as follows.

Step 1: Consider MRI scan image of brain of patients

Step 2: Test MRI scan with the knowledge base

Step 3: Two cases will come forward

i. Tumour detected

ii. Tumour not detected

Step 4: If tumour is detected the severity of tumour is known by classifying them into 3 classes

The architecture of the proposed automatic brain tumour detection and its severity analysis is shown in Fig 1.

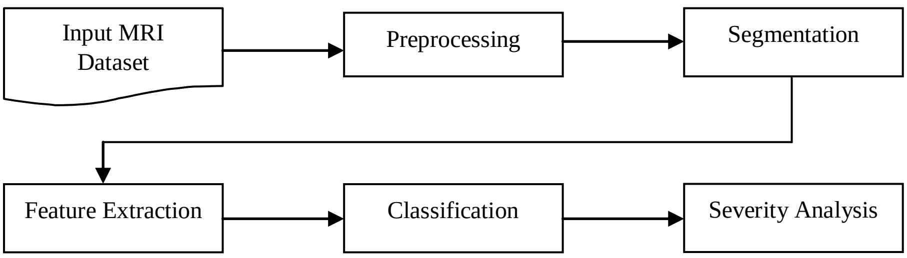


Fig 1: Architecture for automatic brain tumour detection and severity analysis

D. *Pre-processing*

Pre-processing is carried out to make the input images fit for segmentation by removing noise. It is carried out by the use of linear smoothing filters such as median filter. The input MRI image dataset may consist of noise and these noises are removed using median filter. The filter image is useful for further processing like segmentation, feature extraction and classification.

E. *Segmentation*

Image segmentation will partition the brain MRI image into multiple segments. The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyse [14]. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics. The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image [15]. Each of the pixels in a region is similar with respect to some characteristic or computed property, such as colour, intensity, or texture. Segmentation subdivides an image into its constituent parts of objects, the level to which this subdivision is carried depends on the problem being solved, and that is, the segmentation should stop when the edge of the tumour is able to be detected (i.e. the main interest is to isolate the tumour from its background). The main problem in the edge detection process is that the tumour cells near the surface of the MRI is very fat and appears very dark on the MRI, which is very confusing in the edge detection process. To overcome the problem, two steps were performed.

1. Histogram equalization has been applied to the image to enhance the gray level near the edge.

2. Thresholding the equalized image in order to obtain a binarized MRI with gray level 1 representing the tumour cells and gray level 0 representing the background.

Histogram Equalization: These methods usually increase the global contrast of many images, especially when the usable data of the image is represented by close contrast values. Through this adjustment, the intensities can be better distributed on the histogram. This allows for areas of low local contrast to gain a higher contrast. Histogram equalization accomplishes this by effectively spreading out the most frequent intensity values. The method is useful in images with backgrounds and foregrounds that are either bright or dark. The histogram of an image represents the relative frequency of occurrences of the various gray levels in the image. Histogram modelling techniques (e.g. histogram equalization) provide a sophisticated method for modifying the dynamic range and contrast of an image by altering the image such that its intensity histogram has a desired shape.

Thresholding: Thresholding is the simplest method for image segmentation. From a grayscale image, thresholding can be used to create binary images. In many vision applications, it is useful to separate the regions of the image corresponding to objects of interest from the regions of the image that correspond to background. Thresholding, often provides an easy and convenient way to perform this segmentation on the basis of the different intensities or colours in the foreground and background regions of an image. The input to a thresholding operation is typically a grayscale or colour image. In the simplest implementation the output is a binary image representing the segmentation. Black pixels correspond to background and white pixels correspond to foreground. In simple implementations, the segmentation is determined by a single parameter known as the intensity threshold. In a single pass, each pixel in the image is compared with this threshold. If the pixel's intensity is higher than the threshold, the pixel value is set to white in the output. If it is less than the threshold, it is set to black. Segmentation is accomplished by scanning the whole image pixel by pixel and labelling each pixel as object or background according to its binarized gray level.

Image Enhancement: The fundamental enhancement needed in MRI is an increase in contrast. Contrast between the brain and the tumour region present in a MRI may be below the threshold of human perception. Thus, to enhance contrast between the normal brain region and tumour region, a sharpening filter is applied to the digitized MRI, resulting in noticeable enhancement in image contrast.

Morphological Operation: This is used as an image processing tool for sharpening the regions and filling the gaps for binarized image. The dilation operator is used for filling the broken gaps at the edges and to have continuities at the boundaries. A structuring element of 3x3 square matrix is used to perform dilation operation. The region filled operation is used to fill the gaps in the region of interest (i.e. tumour).

Region Extraction: Onto the dilated image, a filling operator is applied to fill the close contours. In filled image, centroids are calculated to localize the regions as shown beside. The final extracted region is then logically operated for extraction of massive region in given MRI image.

IV. FUTURE EXTRACTION

From each co-occurrence matrix, a set of five-features are extracted from different orientations for training the neural network classifier model. Let P be the N*N co-occurrence matrix calculated for the images and then the features are given as follows:

1. Contrast

$$\text{Contrast} = \sum_{i,j=0}^{N-1} (i-j)^2 P(i,j)$$

2. Inverse Difference Moment (Homogeneity)

$$\text{Inverse Difference Moment} = \sum_{i,j=0}^{N-1} \frac{P(i,j)}{1+(i-j)^2}$$

3. Angular Second Moment (ASM)

$$\text{Angular Second Moment (ASM)} = \sum_{i,j=0}^{N-1} P^2(i,j)$$

4. Dissimilarity

$$\text{Dissimilarity} = \sum_{i,j=0}^{N-1} P_{i,j} |i-j|$$

5. Entropy

$$\text{Entropy} = \sum_{i,j=0}^{N-1} P_{i,j} \left(-\ln P_{i,j}\right)$$

V. CLASSIFICATION

A neural network classifier is used to detect candidate circumscribed tumour. The algorithm uses a multi-layer perceptron neural network, the schematic representation of neural network with “n” inputs, “m” hidden units and one output unit. The extracted features are considered as input to the neural classifier. The multi-layer perceptron network architecture is shown in Fig. 2. A neural network is a set of connected input/output units in which each connection has a weight associated with it. The neural network is trained by adjusting the weights, so as to be able to predict the correct class. The desired output was specified as 0 for non-tumour pixel and 1 for tumour pixel. The classification process is divided into the training phase and the testing phase. During training, the features are extracted using Gray Level Co-occurrence Matrix from the images in which the diagnosis is known. Texture features or more precisely, Gray Level Co-occurrence Matrix (GLCM) features are used to distinguish between normal region and brain tumour regions. Five co-occurrence matrices are constructed in four spatial orientations horizontal, right diagonal, vertical and left diagonal (0, 45, 90, and 135) [13]. After training, the trained networks are stored in the algorithm. Whenever an image is taken as input to an algorithm, it is simulated with the trained networks and goes for testing the data [5].

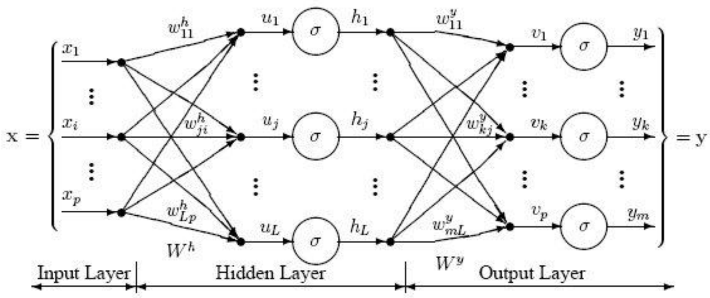


Fig 2: Multi-Layer Perceptron Network Architecture

VI. RESULTS

The data is already trained in the knowledge base. Almost 60 cases of patients are stored in the database; which will be helpful in comparing the MRI image and gives the severity of an image. Sixty brain MR images are used to evaluate the proposed algorithm. The severity of the tumour is known and the different features like Entropy, Angular Second Moment (ASM), Contrast, Inverse Difference Moment (Homogeneity), Dissimilarity are tabulated in Table I. The tumour region in brain is extracted and its severity is analysed and shown in Table II.

Initially, histogram equalization technique is performed. Histogram equalization takes advantage of the neglected pixel values and provides better definition. Segmentation is followed after histogram equalization to segment tumour regions from the image; further it provides better means to assess the tumour region in MRI images. The algorithm developed automatically calculates the threshold for the images. Edge detection algorithms are able to detect the tumour region very well. Mathematical morphology act as a tool for extracting image components, which are useful for the representation and description of region shape such as boundaries, etc. Also morphological techniques for pre- and post-processing, such as morphological filtering and dilation is also adopted.

The application of neural networks models in non-invasive abnormality diagnosis, using sample images, represents a promising complementary method, enhancing and supporting the differential diagnosis of normal tissue and abnormalities. Initially MRI image is loaded as an Input Image (abnormal MRI Input) and Multi-Layer Perceptron Neural Network is used detect the image as cancer affected image for normal brain.

TABLE I Statistical analysis of Texture features of a MRI Image with the tumour

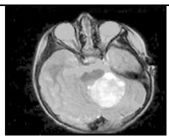
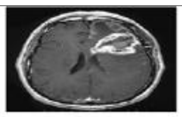
MRI Images	**MRI Image of brain**	**Angular Second Moment (ASM)**	**Contrast**	**Inverse Difference Moment (Homogeneity)**	**Dissimilarity**	**Entropy**
Image 1		3304	3476	0.15	1985	-64.12
Image 2		5943	1934	0.01	3707	-49.76
Image 3		2303	1245	0.43	2075	-73.36

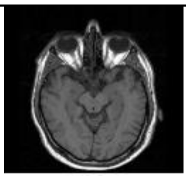
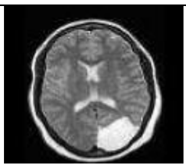
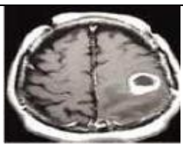
Image 4		6799	3452	0.17	2937	-76.95
Image 5		7392	1623	0.27	1824	-58.63
Image 6		3259	3846	0.09	1572	-46.34
Image 7		2789	3754	0.19	3283	-82.48

TABLE III MRI image of brain, its extracted tumour and its severity of disease

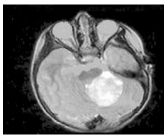
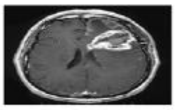
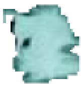
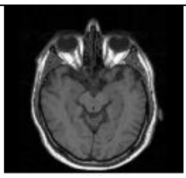
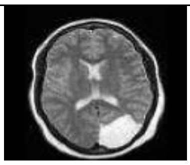
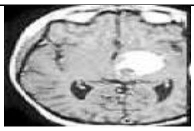
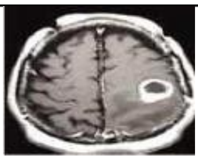
Data set	**MRI Image of brain**	**Extracted Tumor**	**Severity of disease**
Image 1			Class 2 Anaplastic Astrocytoma will grow faster
Image 2			Class 3 Glioblastoma multiforme (GBM) most invasive type of tumor, commonly spreads to nearby tissues grows rapidly.
Image 3			Class 2 Anaplastic Astrocytoma will grow faster
Image 4		No tumor	No tumor
Image 5			Class 3 Glioblastoma multiforme (GBM) most invasive type of tumor, commonly spreads to nearby tissue, grows rapidly.
Image 6			Class 1 Astrocytoma is slow growing, rarely spreads to other parts of the CNS, Borders not well defined.

Image 7			Class 3 Glioblastoma multiforme (GBM) most invasive type of tumor, commonly spreads to nearby tissue, grows rapidly.

VII. Conclusion

The proposed approach for brain tumour detection and its severity analysis is based on artificial neural network categorized into Multi-layer perceptron neural network. The proposed approach utilizes a combination of this neural network technique and is composed of several steps including segmentation, feature vector extraction and model learning. The purpose of this paper is to develop tools for discriminating the two classes normal and abnormal from MRI input Scanner and assist on decision making in clinical diagnosis and this will help doctor to take or analyse in which stage of cancer the patient have and according to which he/she can take necessary and appropriate treatment steps. This work has introduced as one automatic brain tumour detection method and severity analysis to increase the accuracy and yield and decrease the diagnosis time. The proposed system requires effective image has to be chosen for opting better segmentation techniques. Early detection of the tumour will be useful to the patients for who has smaller tumours that are class 1 and class 2 tumours, which can be cured easily if treated at early stages.

References

1. Cline HE, Lorensen E, Kikinis R, Jolesz F, "Three Dimensional segmentation of MR images of the head using probability and connectivity", J Comput Assist Tomography 1990; 14:1037–1045.
2. Vannier MW, Butterfield RL, Rickman DL, Jordan DM, Murphy WA, Biondetti PR, "Multispectral magnetic resonance image analysis", Radiology 1985; 154:221–224.
3. Just M, Thelen M, "Tissue characterization with T1, T2, and proton-density values: results in 160 patients with brain tumors", Radiology 1988; 169:779–785.
4. Just M, Higer HP, Schwarz M, et al, "Tissue characterization of benign tumors: use of NMR-tissue parameters", Magn Reson Imaging 1988; 6:463–472.
5. Gibbs P, Buckley DL, Blackband SJ, Horsman A, "Tumor volume determination from MR images by morphological segmentation", Phys Med Biol 1996; 41:2437–2446.
6. [6] Velthuizen RP, Clarke LP, Phuphanich S, "Unsupervised measurement of brain tumor volume on MRI images", J Magn Reson Imaging 1995; 5:594–605.
7. Vinitski S, Gonzalez C, Mohamed F, "Improved intracranial lesion characterization by tissue segmentation based on a 3D feature map", Magn Reson Med 1997; 37:457–469.
8. Collins DL, Peters TM, Dai W, Evans AC, "Model based segmentation of individual brain structures from MRI data", SPIE VisBiomed Comput 1992; 1808:10–23.
9. Kamber M, Shinghal R, Collins DL, "Model-based 3-D segmentation of multiple sclerosis lesions in magnetic resonance brain images", IEEE Trans Med Imaging 1995;14:442–453.
10. Warfield SK, Dengler J, Zaers J, "Automatic identification of gray matter structures from MRI to improve the segmentation of white matter lesions", J Image Guid Surg 1995; 1:326–338.
11. Warfield SK, Kaus MR, Jolesz FA, Kikinis R, "Adaptive template moderated spatially varying statistical classification", In: Proceedings of the First International Conference on Medical Image Computing and Computer-Assisted Intervention. Boston, Mass: Springer-Verlag, 1998; 431–438.
12. Bonnie NJ, Fukui MB, Meltzer CC, "Brain tumor volume measurement: comparison of manual and semi-automated methods", Radiology 1999; 212:811–816.
13. Aniket A. Kathalkar, R. S. Kawitkar, Amruta Chopade, "Artificial Neural Network based Brain Cancer Analysis and Classification", International Journal of Computer Applications (0975 – 8887).
14. Linda G. Shapiro and George C. Stockman, "Computer Vision", New Jersey, Prentice-Hall, ISBN 0-13-030796-3, pp 279-325, 2001.
15. Sudipta Roy, Samir K. Bandyopadhyay, "Detection and Quantification of Brain Tumor from MRI of Brain and its Symmetric Analysis", International Journal of Information and Communication Technology Research.
16. P. John, "Brain Tumor Classification Using Wavelet and Texture Based Neural Network", International Journal of Scientific & Engineering Research, Vol. 3, Issue 10, pp. 1-7, 2012.
17. J. Kaur, S. Agrawal and R. Vig, "A Comparative Analysis of Thresholding and Edge Detection Segmentation Techniques ", Int. Journal of Computer Applications., Vol. 39, Issue 15, pp. 21-34, 2012.

18. Manoj K Kowar, Sourabh Yadav, "Brain Tumor Detection and Segmentation Using Histogram Thresholding", International Journal of Engineering and Advanced Technology, Vol. 1, Issue4, pp. 2249– 8958, 2012.
19. N. Senthilkumaran and R. Rajesh, "A Study on Split and Merge for Region based Image Segmentation", Proceedings of UGC Sponsored National Conference Network Security, pp.57-61, 2008.
20. Ahmed kharrat, Karim Gasmi, "A Hybrid Approach for Automatic Classification of Brain MRI using Genetic Algorithm and Support Vector Machine", Leonardo Journal of Sciences, pp.71-82, 2010.