

Applications of Object Detection, Brain Tumor Detection and Classification

Bhagyalakshmi A ^{a,1}, Deepa S ^b and Parthiban N ^c

^a *Department of Computer Science and Engineering, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Chennai*

^b *Department of Computer Science and Engineering, SRM institute of science and technology, Chennai*

^c *School of Computing Science and Engineering, Galgotias University, Greater Noida, Delhi-NCR*

Abstract. In the medical diagnosis system, detection and labelling of the specific region of interest and classification of diseases in Computer Tomography (CT) images and Magnetic Resonance Imaging (MRI) scans is a challenging task. Another major application is tumor or cancer type of cell detection as well as finding its size and location in the image. This research work focuses on addressing the most challenging research gaps existing in the field of medical diagnosis such as brain tumor identification in medical images, retrieving similar images or region from the database. In these applications, the major task involved in the extraction of sufficient and relevant features, is to identify the region of interest. With the extracted features development of efficient algorithms for the detection of region of interest (ROI) and the learning algorithms also required to classify the new images for the existing features. The highlight of the proposed work is to design an automated detection of the presence of tumor cells in the brain image and classification of normal and abnormal brain images.

Keywords. DWT, k-means clustering, LBP, GLCM, Neural Network.

1. Introduction

Applications of object detection play a major role in different domains including medical diagnosis, biometrics, industry inspection, geographical information satellite systems, 3D object identification, web searching and historical research and so on [1–3]. In the medical environment, day by day the size of medical images like CT and MRI images increases continuously [4]. The applications involving images face more challenges and crucial problems such as storage management, indexing, knowledge management, and content understanding. It requires an efficient recognition mechanism to process and learn the region of interest from a different database [5–7]. The techniques developed in the area of target object detection, attempts to solve the problems associated with it and return a set of objects from the database based on similarity features like color, shape, and

¹Bhagyalakshmi A, Dept. CSE, Vel Tech Rangarajan Dr.Sagunthala R&D Institute of Science & Technology. E-mail: annappanbhagyalakshmi@gmail.com.

texture. In geographical information satellite systems, content-based retrieval of remote sensing images for analysis is effectively used. Statistics of the global burden of cancer across the world have been given by researchers, using the GLOBOCAN 2018 –

International Agency for Research on Cancer, with a focus across 20 world regions. Advancements in cancer prevention, early detection, and treatment, have resulted in a 23% drop in the cancer death rate, from a peak of 215.1 (per 100,000 populations) to 166.4 in 1991. Medical diagnosis at an early stage requires efficient image processing algorithms that are applied to various image modalities like CT and MRI. The high contrast of soft tissues and spatial resolution nature of Magnetic Resonance Imaging (MRI) helps in making the segmentation process easier. These segmentation results are applied to various medical diagnoses like disorders, epilepsy, Alzheimer's disease, schizophrenia, Parkinson's disease, cerebral atrophy, etc. Jimenez-Alaniz (2006) proposed non-parametric density estimation, using the Mean Shift (MS) algorithm. With joint space-range density function cluster points are detected. The cluster class boundaries are improved by edge confidence map that truly maps the pixels with adjacent regions and it is an iterative approach that enhances by Region Adjacency Graph (RAG). Kass et al. (1988) used deformable models for region boundary detection. The region growing methods are formulated from homogeneity and connectivity points. In this method initial seed points are identified, then adjacent points are collected depending on the homogeneity and similarities in intensity. These methods are depending on level set and energy functions. Due to complex structures in medical images, these techniques additionally involve the statistical feature models to improve accuracy. The following challenges are exist in designing an object recognition and image retrieval system such as presence of noise and background intensity variations make analysis of brain tumor complicated, identifying a fitting segmentation algorithm to distinguish the tumor mass in a brain image, identification of tumor mass regions with in the segmented regions, identification of suitable feature descriptor to enable classification of normal and abnormal image and Absence of automated diagnosis system to identify the cancerous brain image.

2. Proposed system for brain tumor identification

This paper work intends to suggest an algorithm to extract meaningful and accurate information by which effective identification of tumor cells in the brain image. This includes, design and implement an algorithm for pre-processing of MRI images such that removal of streak artifacts, design and implement a segmentation algorithm and locate the affected mass region in an image, design a texture measure algorithm to differentiate the images, design an accurate classifier to compare the defected and normal images and design an algorithm to carry out automated detection of tumor regions and proper measure to measure the region statistical features. The main tasks of the proposed system include, Gaussian smoothening, median filter and template matching which are used to enhance the image by removing noise and smoothening the edges, Discrete Wavelet Transform (DWT) is used for the reduction of dimensionality, k-means clustering algorithm and morphological operators are used to perform image partitioning, Texture feature in an image is extracted using Gray Level co-occurrence Matrix (GLCM) and Local Binary Pattern (LBP) operators, Euclidean distance metric is used for similarity measures, Precision and recall measures are used to evaluate the performance of the diagno-

sis system with brain MR images [8]. The Figure 1 describes the architecture diagram of the proposed work. Initially when the MRI images from the database is passed to the classification system, it is transformed into uniform scale. Gaussian filter and template matching used for the removal of streak artifacts to further enhance the image. The transformed image is partitioned using ‘k-means clustering’ algorithm in a gray scale form of the input image. The above-mentioned algorithm is best used to scrutinize regions of the image effectively, yet may consist of a few false regions that are needed to be checked. The morphological operators are put to use extensively, to avoid additional false regions present in the image by applying the dilation mask. Once the image is converted into a binary image, the false regions present in the true region are removed using fill holes function. The image is now prepared to go through further steps in object extraction. The boundaries of every region are extracted and these regions are stored in the object vector. In order to classify the images, features descriptor is derived for the regions stored in the object vector .the feature descriptor describes the texture properties as well as region properties of the image. Using these descriptors, the dataset is constructed for neural network. To get more accurate results, the neural network is trained using 75 examples to classify the normal and abnormal images.

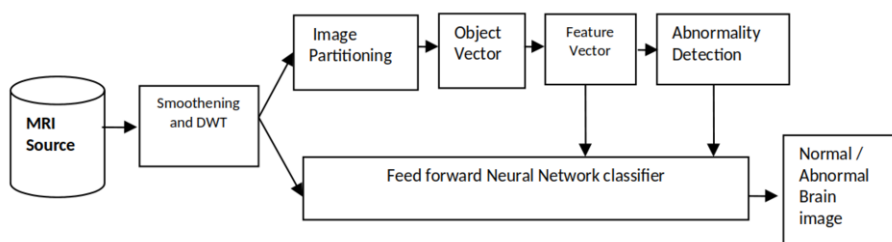


Figure 1. Overall process flow of the proposed system

3. Methodology to extract tumor region and classification of MRI

3.1. Removal of Noise

MRI images captured usually are prone to Gaussian noise and salt and pepper noise which has influence on the MRI image quality [9, 10]. The Poor quality of MRI image tends to degrade the performances of any works such as feature extraction, reduction and classification of the processed MRI images. The Gaussian smoothing, median filter and template matching provides a high performance in removing streak artifacts and background noise [11].

3.2. Dimensionality Reduction using DWT

For the storage reduction and to improve the computational complexity, two-dimensional Discrete Wavelet Transform (DWT) is applied for the image [12, 13]. It decompose the image is into mutually orthogonal wavelet basis functions. These wavelet functions are translated, scaled and dilated versions of mother wavelet Φ . DWT generates two kinds of

coefficients namely approximation coefficients and detail coefficients. These are generated using low pass filter and high pass filter. From these coefficients when it is applied to column wise it generates four sub bands such as LL,LH,HL,HH. The Figure 2 shows the generation of four sub bands from the input image. The more detailed information exists in LL sub band so that it is used for the remaining processing techniques.

3.3. *k-means Clustering Algorithm*

k-means clustering act as an appropriate algorithm for brain image segmentation and performs crisp partitioning. This algorithm is used to segment the image, even the image contains shadowing, noise and camera variations in the image. This algorithm takes image as a argument and which is represented as a n-dimensional vector space. it returns the set of clusters which include the corresponding pixels based on the similarity of neighbour pixel value. Euclidean distance metric values are calculated between the pixel and centroid of the clusters to classify the pixels.

3.4. *Morphological Operators- Erosion and Dilation*

When the image is segmented in to clusters, the image is converted in to binary image. This segmented image consists of additional noise and smaller holes that is not belongs to region of interest. These problems rectified by performing image smothering using morphological operators such as opening and closing.

3.5. *Neural Network Classifier*

To classify the normal and abnormal brain images the probability based classifier is required to detect the brain tumor at early stage. the feed forward neural network is a efficient type of NN-classifier, act as an appropriate algorithm for classification of medical images. The texture metric very much useful for the clasification of images because of the variation in the intensity levels, this is measured by computing LBP histogram and GLCM. the images stored in the database divided into training and testing images. For all suspected and normal brain images the texture features are calculated and the set of texture properties are retrieved from the LBP histogram and GLCM measures. The most prominent feature metrics are idetified to classify the nomal and defected images. The input vector and output vectors are constructed with the labels such as normal and abnormal to train the neural network is effectively.

3.6. *Texture Metrics – LBP & GLCM*

Local Binary Pattern (LBP) - this technique approximates the variation in the texture by comparing the center pixel with the neighbouring pixels. It is used to detect the local patterns in an image. LBP code is calculated using 3 x 3 neighbourhoods with center pixel acting as a threshold. First, it calculates the gray scale difference and the difference are multiplied with weights of the corresponding pixels. Given an image for each pixel, an LBP code is computed by the Eq. (1) and Eq. (2) as,

$$LBP_{P,Q} = \sum_{i=0}^{p-1} 2^i f(g_i - g_c) \quad (1)$$

$$f(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{else} \end{cases} \tag{2}$$

Where $f(g_i - g_c)$ function applied to the gray level difference, g_c is the intensity value of the center pixel, g_i is the intensity value of its neighbours, P is the total number of neighbours involved and Q is the radius of the neighbourhood. In order to construct feature vector for texture classification, cumulative LBP histogram is constructed. The statistical measures such as mean, variance, standard deviation, entropy, skewness and kurtosis are calculated from the constructed LBP histogram and represented as a feature vector for classification of images.

3.7. Gray Level Co-Occurrence Matrix (GLCM))

In GLCM the texture metrics is measured by considering the spatial existence between the pixels of statistical method.texture vlaues are computed by pairs of specific values and ina specified spatial relationship occur in an image,thus creates a GLCM vector of textures values between the pixels [14]. From the GLCM vector statistical measures contrast, correlation,energy and homogeneity are computed and represented as feature vector for classification.

4. Implementation results and performance analysis

Nearly 100 MRI based brain images are collected from different patients . The images have been reviewed by a consultant radiologist to identify abnormalities and truth data is available with the database. Images are numbered conveniently from 1 to 100. The information from the radiologist is taken as reference standard for checking accuracy of results presented in this research work. The entire work is implemented in MATLAB.

4.1. Dimensionality Reduction by DWT

Initially the filtering and smoothening techniques are applied to remove the noise and streak artifacts in an image. Then the processed image is reduced using DWT and generated four sub bands namely LL, LH, HL, HH using low pas and high pass filters. The Figure 3 shows the sub bands generated for the reference brain image.

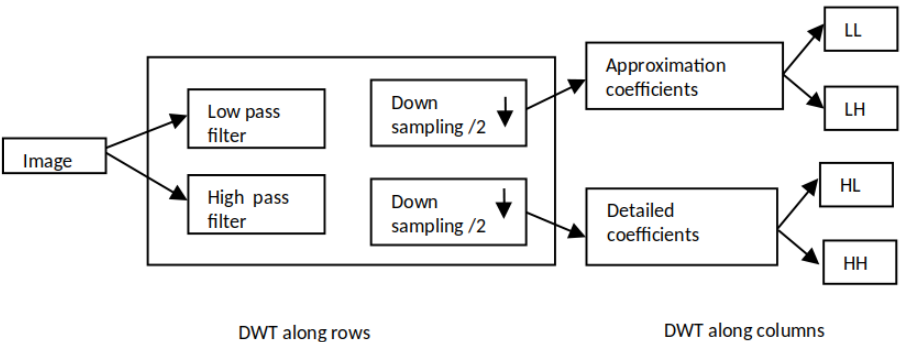


Figure 2. Frequency Band extraction Using DWT

4.2. Image Segmentation and Tumor Region Detection

The pre-processed image is partitioned in to different clusters using k-means clustering technique [15]. The following Figure 4 shows the segmented image for the reference image. The segmented is smoothened by morphological operators using erosion and dilation function. [16–19] The defected region is identified by filling holes in the binary image. Brain tumor regions are extracted from the image and region properties such as Area, Perimeter, bounding box, Extent and Eccentricity are calculated to identify the spreading level of tumor cell occupied in the brain for the evaluation of brain tumor diagnosis. Figure 6 shows the tumor regions properties and its values. Accuracy or correct rate of classification is the efficiency of appropriate identification to the total number of images and it is defined by the Eq. (3) as,

$$Accuracy(\%) = \frac{CorrectIdentification}{TotalNumberofImages} * 100 \quad (3)$$

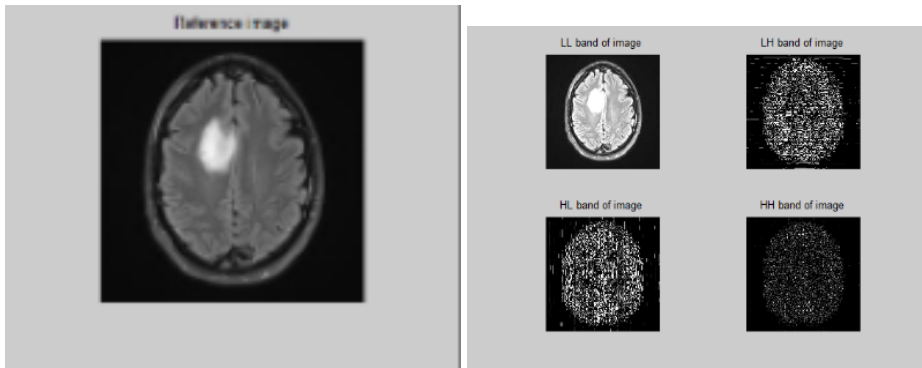


Figure 3. Frequency Band extraction for the brain reference image

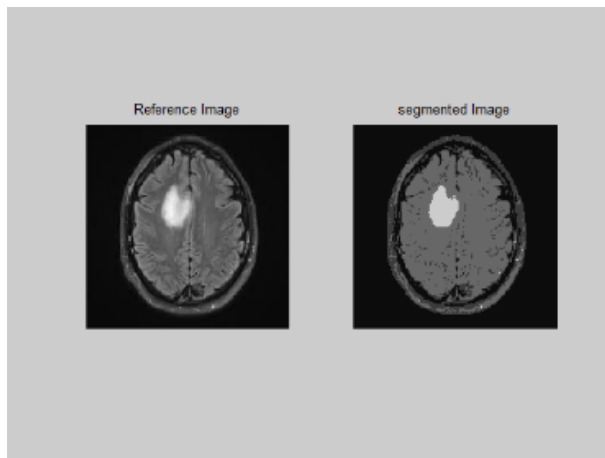


Figure 4. Reference and segmented image

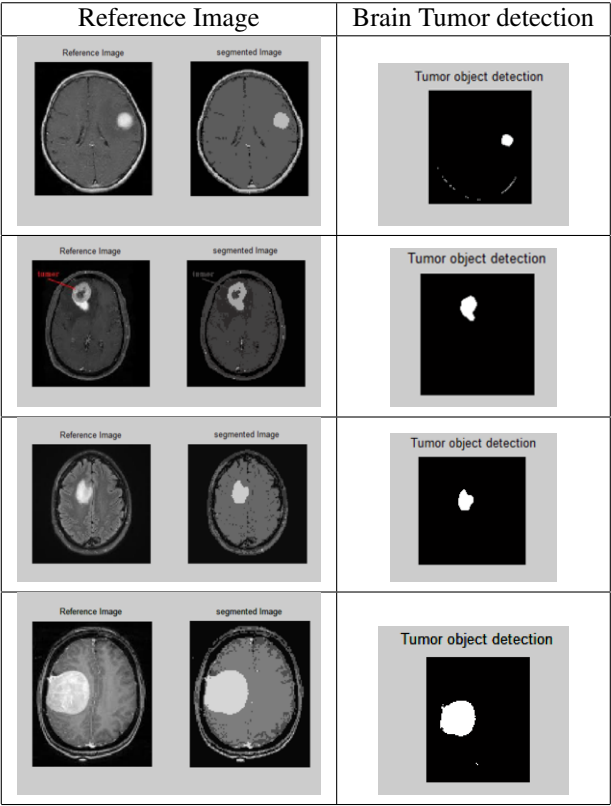


Figure 5. Detection of Brain Tumor Region

4.3. Activation of Neural Work for the Classification of Images

For every normal and defected image stored in the database texture features are extracted using LBP histogram and GLCM and labelled as normal and abnormal respectively. The Table 1 and 2 describes the sample-extracted features for the brain images. The feed forward neural network is trained using the input and output vectors of the feature vector [20].

Table 1. GLCM- Textural statistical features

S.No.	Trained Images	GLCM- Statistical Features				Label
		Contrast	Correlation	Energy	Homogeneity	
1	Image 1	0.302	0.964	0.204	0.901	Normal
2	Image 2	0.403	0.906	0.262	0.901	Normal
3	Image 3	0.161	0.912	0.353	0.936	Normal
4	Image 4	0.291	0.949	0.228	0.906	Abnormal
5	Image 5	0.401	0.895	0.270	0.902	Abnormal
6	Image 6	0.151	0.863	0.358	0.938	Abnormal




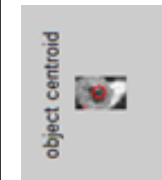
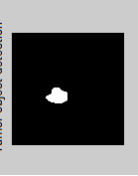

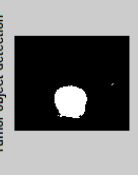
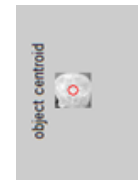
Brain Tumor detection	Tumor Object Centroid	Area	Perimeter	Bounding Box	Extent	Eccentricity
		141	40.57	[0.5,0.5,12,13]	0.90	0.41
		257	64.77	[0.5,0.5,16,24]	0.66	0.75
		254	64.95	[0.5,0.5,16,24]	0.66	0.75
		844	104.3	[0.5,0.5,31,31]	0.87	0.27

Figure 6. GLCM- Textural statistical features

4.4. Analysis of Classification Accuracy

Feed forward neural network was used for training and testing purposes. Training was carried out using 75 MR images which consists of both normal and abnormal brain images. From GLCM and LBP statistical features, four parameters are selected to classify the network, namely contrast, correlation, homogeneity and entropy. For the neural network, input layer consisted of 10 neurons and an output layer had a single neuron, to represent binary classification. Binary ‘0’ represents normal MRI and Binary ‘1’ represents abnormal MRI. Number of neurons in hidden layer of this network found to have an

Table 2. LBP – Textural statistical features

S.No.	Trained Images	LBP- Statistical Features				Label
		Entropy	SD	Skewness	Kurtosis	
1	Image 1	0.219	495	10.92	148.75	Normal
2	Image 2	0.272	976	14.22	217.99	Normal
3	Image 3	0.289	876	13.98	212.67	Normal
4	Image 4	0.091	489	10.93	148.80	Abnormal
5	Image 5	0.237	967	14.22	217.94	Abnormal
6	Image 6	0.242	850	13.96	211.70	Abnormal

impact on classifier accuracy. By varying number of hidden layer neurons, classification accuracy was plotted. Figure 7 shows the accuracy results for the training and test images by the proposed neural network. Results of neural network show that 90% accuracy so that tumor region is extracted quite accurately.

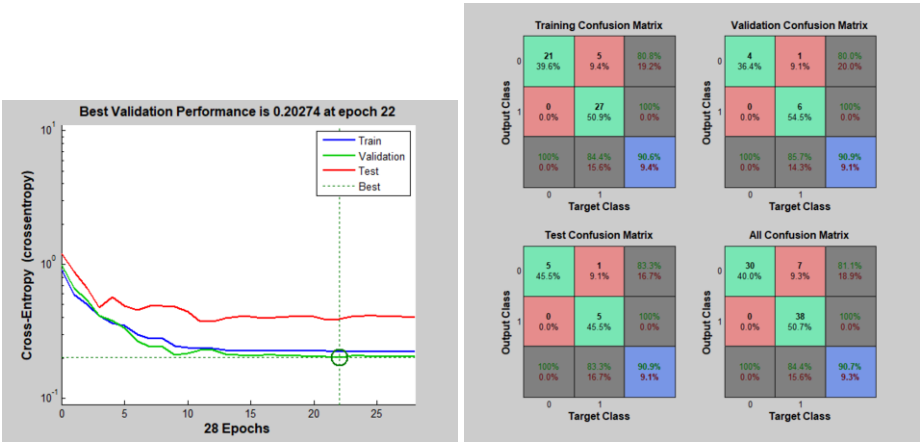


Figure 7. Classifier -Performance results and confusion matrix

5. Conclusion

This paper focuses on early detection of affected brain regions in order to reduce the death rate due to brain tumor world wise. To support this research work, five different patients MR images of various stages of tumor are used and trained to identify the tumor regions effectively. The stored MR images in the database are pre-processed by Gaussian and median filter to remove noise that improves the performance measures and reduces the error rate during classification. The k-means segmentation algorithm detect the brain region effectively. The Morphological operators are used to remove the unwanted objects exits in the image. Overall this dilation process identified the brain tumor regions efficiently. Using the features of tumor region properties the level tumor occupied in the brain can be effectively determined and it is useful for the doctors to make the diagnosis process is easier. The neural network, which classifies the normal and defected brain images effectively using the feature vectors which is constructed by LBP and GLCM

texture measures. In future, this research work is extended to identify the cancer cells in the stomach and lungs.

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