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Automatic Brain Tumor Detection using Super pixel zoning and DWT

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Abstract: Earlier is the diagnosis of a disease; better is the rate of recovery. As far as the pestilent disease like brain tumor is concerned, its early identification may lead to improve the rate of care and thereby benefitting the survival of a patient. Typically, brain tumor detection and analysis starts from the process of brain MRI segmentation. This segmentation partitions the potentially overlapping parts in the internal structure of the brain into brain tissues such as White Matter (WM), Grey Matter (GM) and Cerebro Spinal Fluid (CSF). In this paper, automated brain tumor detection has been proposed for detecting the presence/ absence of brain tumor from brain MR images. Relevant pre-processing is applied to input brain MR images. Firstly, the brain input image is zoned using superpixel zoning and brain tissues are being segmented using discriminative clustering. Secondly, feature extraction is done using level 2 2-D discrete wavelet transform to generate the matrix vectors. AdaBoost with random forests algorithm (ADBRF) is used as its base classifier to classify the given brain MR image into normal or abnormal. Simulation results are compared with the existing methods on BrainWeb brain MRI dataset and it is observed that the proposed scheme outperforms other state of the art methods.

Keywords: Automated brain tumor detection, Discrete wavelet transform (DWT), and BrainWeb.

1. INTRODUCTION

Human brain is a soft, delicate, irreplaceable and spongy mass of a tissue [2]. Human body made up of cells which performs cell division to promote the growth of the body. These cells sometimes lose the control on growth of these cells leading to abnormal growth of these cells forms a mass of tissue called "tumor". These tumors damages healthy cells causing inflammation, brain swelling and pressure within the skull. Tumors can be categorized into 3 types namely benign, pre-malignant, and malignant. Benign tumors are tumors that doesn't cause any harm. Pre-malignant tumors are tumors which are in the primary stage of causing cancer. Malignant tumors are tumors which are of greater severity and that may leads to death. Out of all cancer deaths in children, one quarter are because of presence of brain tumors. According to reports of National Cancer Institute statistics (NCIS), brain tumor cases are increased by 10% across the world. Out of 29,000 who diagnosed with brain tumor in United States, nearly 13,000 people have died. So, there is a need of early identification of the disease. Brain tumors can be formed in two ways, primarily due to abnormal growth of cells in the brain and secondarily it can spread from the tumors from other parts of the day.

Detection and delineation of brain tumor within a MR image is a vital problem in medical image analysis and clinical diagnostics. In medical sciences, imaging is a vital aspect in visualizing the internal structures of the human body. Automated Brain detection is one of the active research topics in the discipline of image processing. Image processing can be defined as the process of applying computing techniques on images to extract useful information from them [13]. Various medical imaging techniques such as ultrasound, magnetic resonance imaging (MRI), X-ray, make use of computing technology to generate the digital images of the human body parts. These multidimensional digital images of physiological structures are processed using different computing algorithms to visualize the diagnostic features of the internal structures of the human body. MRI is the state of the art imaging technique which provides cross sectional view of the brain with impeccable contrast and this makes MR images an ideal source for detecting, identifying and classifying the infected regions in the brain [4].To visualize these structures of the brain, segmentation of these images need to be carried out.

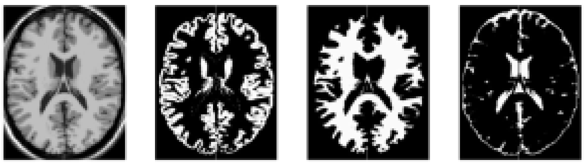

Figure.1 Partial volume effect in MRI segmentation.

Segmentation can be described as the partitioning the image into various mutually exclusive regions which

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shows homogenous features. Segmentation is broadly divided into three categories namely, edge-based methods, region-based methods, and pixel-based methods [14]. Superpixel zoning is a pixel based method of segmentation, where a group of pixels having same intensity values are grouped to form a superpixel. However, manual interpretation of large volumetric data is time consuming which leads to delay treatment workflow. Also, manual annotations may differ from one medical expert to other as difference in individual experience and in interpretations. So, there is a need for automatic segmentation of brain MR images to perform brain tumor detection. Although, automatic segmentation is very useful in medical imaging analysis and clinical diagnostics; it faces three severe challenges such as acquisition noise, partial volume effect and bias field. Acquisition noise arises as one cannot expect ideal conditions while MRI scan is carried out [19]. Partial volume effect arises as brain internal structure of potentially overlapping parts with heterogeneous features in every region. Bias field effect occurs due to non-uniform magnetic fields or magnetic susceptibility.

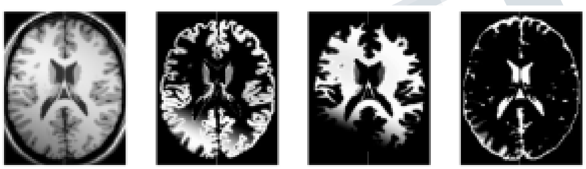

Figure.2 Bias field effect in MRI segmentation.

The remainder of the paper is organized as follows. In section Ⅱ, a review of the necessary background required to effectively implement our algorithm is presented. The proposed algorithm is described in Section Ⅲ. After that, simulation of the proposed algorithm is discussed in section Ⅳ, and we draw our conclusion in the last section.

II. LITERATURE SURVEY

In this section, we briefly review the proposed automatic brain tumor detection algorithms. Ming-Ni Wu et al. [1] proposed a color-based segmentation method that uses the K-means clustering technique to track tumor objects in magnetic resonance (MR) brain images, here the gray level brain MR image is converted into color image and segregate the position of tumor from other objects in the image using k-means and histogram classification. Logeswari et al. [2] proposed an improved implementation of brain tumor detection using segmentation based on hierarchical self-organizing map (HSOM); here brain MR image segmentation is carried out fuzzy C-Means clustering algorithm to identify principal tissue structures of the brain. Vrushali Borase et al. [3] proposed brain MR image segmentation for tumor detection using artificial neural network: here noise is removed from the input brain MR image using a high pass filter, [12] segmentation is done using k-means and thresholding and finally classification is done using artificial neural network. Dina Aboul Dahab et al. [4] proposed a modified Probabilistic Neural Network (PNN) model that is based on learning vector quantization (LVQ) with image and data analysis and manipulation techniques is proposed to carry out an automated brain tumor classification using MRI-scans. Karnan et al [5] proposed an improved implementation of brain tumor detection using segmentation based on soft computing where it uses HSOM algorithm to classify the image row by row and it resulted in a higher value of tumor pixels and greater computation speed. Michael Wels et al. [6] proposed a discriminative model-constrained graph cuts approach to fully automated brain tumor segmentation in 3-D MRI, It is a top-down segmentation approach based on a Markov random field (MRF) model that combines probabilistic boosting trees (PBT) and lower-level segmentation via graph cuts. Matthew C. Clark et al. [7] proposed a system that automatically segments and labels tumors in magnetic resonance images (MRI's) of the human brain where it uses an unsupervised algorithm as an initial segmentation and Multispectral histogram analysis to separate the tumor from intracranial region. Rahul Isola et al. [8] proposed a knowledge discovery in medical systems using differential diagnosis, LAMSTAR, and k-NN, this system uses a service-oriented architecture wherein the system components of diagnosis, information portal, and other miscellaneous services are provided. Anupurba Nandi et al. [9] proposed a system where it uses K-Means clustering for initial segmentation, it results in detected tumour which shows some abnormality which is then rectified by the use of morphological operators and to separate tumour cells from the normal cells. N. Nandha Gopal et al. [10] proposed an intelligent system to diagnose brain tumor through MRI using image processing clustering algorithms such as Fuzzy C Means along with intelligent optimization tools, such as Genetic Algorithm (GA), and Particle Swarm Optimization (PSO). Abdul Kalam Abdul Salam et al. [11] proposed an assessment on brain tumor detection using rough set theory. Rough set theory is used for the discovery of data dependencies, importance of features, patterns in sample data, and feature space dimensionality reduction. Fletcher-Heath et al. [15] use unsupervised fuzzy

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clustering followed by 3-D connected components with an intermediate step incorporating knowledge about the usual distribution of cerebral spinal fluid and location of the ventricular system. Gering et al. [16] use trained parametric statistical models for intensity distributions of non-pathologic brain tissue to detect model outliers on the voxel level that are considered tumor voxels in a multi-layer Markov random field framework. Prastawa et al. [17] detect outliers based on refined intensity distributions for healthy brain tissue initially derived from a registered probabilistic atlas, which introduces structural domain knowledge. Registration is also used in combination with voxel intensities in the adaptive template-moderated classification algorithm by [18].

III. PROPOSED WORK

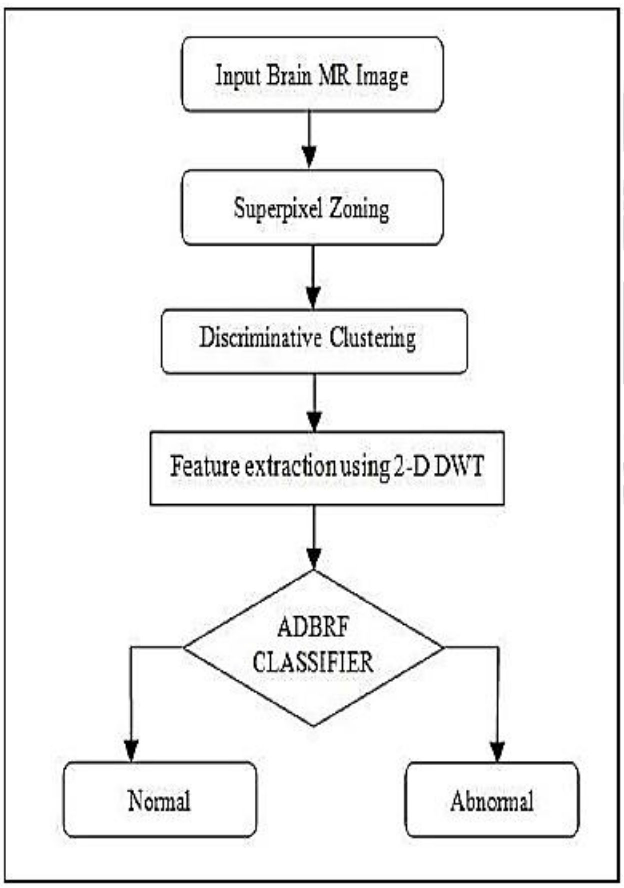

Figure.3 System Architecture.

Figure.3 has shown the architecture of the proposed algorithm. Firstly, an input brain MR image is preprocessed using superpixel zoning. The image is zoned into homogenous regions by the means of superpixel zoning algorithm. Secondly, these superpixel zoned regions are then clustered using discriminative clustering method forms a preprocessed input brain MR image. Thirdly, a 2-d discrete wavelet transform is applied to the segmented image to extract features from it. Fourthly, the AdaBoost with random forests classifier is used as its base classifier and using extracted features it build a classifier; the classified brain tumor image is outputted at last. The rest parts of this section will discuss the details.

A. Preprocessing

A Superpixel is an image patch which is better aligned with intensity values of edges than a rectangular patch. Superpixels can be extracted with any segmentation algorithm however most of them produce highly irregular superpixels with wide variety of sizes and shapes. If you consider an image grid of same intensity values and also neighborhood values which together grouped to form a superpixel. Superpixels are becoming highly popular in medical image analysis applications. Although they are popular, they face challenges such as high computational cost, poor quality segmentation, inconsistent size and shape [1]. Superpixels are used in applications such as depth estimation [12], image segmentation [13, 14], skeletonization [15], body model estimation [16], and object localization [17]. Superpixels provide us ability to capture local image features and capture redundancy there by reducing computational complexity. Superpixels extract homogenous features so they account for bias field. The simple linear iterative clustering (SLIC) [5] method is used to generate 2D superpixels for brain MRI. The superpixel level zoning algorithm consists of nine steps:

1) Initialize cluster centers Ck by sampling pixels at regular grid steps S.
2) Perturb cluster centers in an n x n neighbourhood, to the lowest gradient position.
3) repeat
4) for each cluster center Ck do
5) Assign the best matching pixels from a 2S _ 2S square neighbourhood around the cluster center according to the distance measure.
6) end for
7) Compute new cluster centers and residual error E {L1 distance between previous centers and recomputed centers}.
8) until E ≤ threshold
9) Enforce connectivity.

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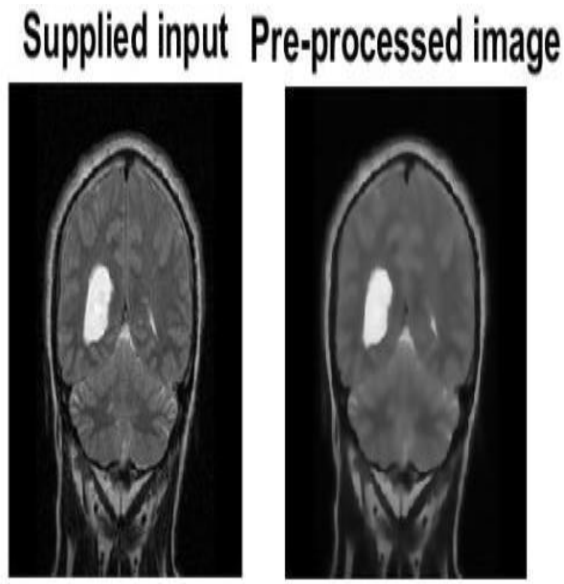

Figure.4 preprocessed brain MR image.

B. Feature extraction using DWT

The Discrete Wavelet Transform (DWT) is a powerful method for feature extraction [6] and it has numerous applications in audio compression, pattern recognition, texture discrimination, computer graphics etc. DWT provides efficient multi-resolution sub band decomposition of images using time scale representation, which is very useful in classification scenarios [7]. DWT is accepted as new compression standard JPEG2000. The DWT passing a signal into an image using 2 filters, a low pass filter and a high pass filter. The low pass filters extract low resolution signal whereas the high pass filters extract difference signal. The output signals are samples are down sampled by two and these down samples outputs have same number of bits as the input signal. The output of the high pass filters are sent into to another pair of filters and process repeated [7]. Haar wavelet is the best suitable dwt for the classification process as it is very fast, symmetric and orthogonal in nature, it also used to extract structural information from the images and performs well in the presence of noise. DWT is decomposed in this process up to 3 levels. Firstly, an image of size N X N is decomposed to N/2 X N/2 of four sub bands namely, LL (low-low), LH (low-high), HL (high-low) and HH (high-high). The LH, HL and HH are the sub-band images that contain the edges in the vertical, horizontal and diagonal directions respectively. The LL sub-band image is the approximation image contains maximum information, so it is fed into next level for 2D DWT calculations.

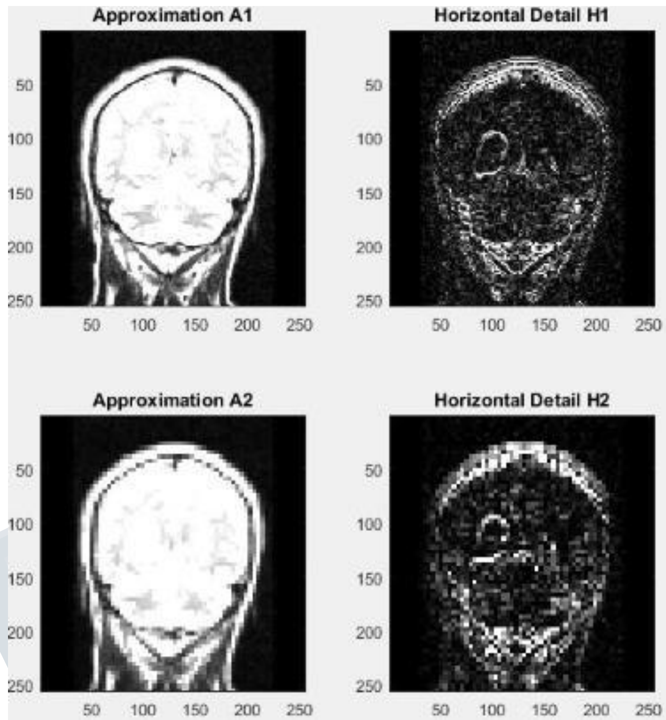

Figure.5 feature extraction using dwt.

C. Proposed Algorithm

Input: Brain MR Image dataset (D) with each sample (di), with dimension M x M.

Output: Feature Matrix (f).

Step 1: Initialize f→ ф

Step 2: Repeat for each image (I).

Step 3: Put X superpixel seed points.

Step 4: Label each pixels using

D (x, l) = I (x, l) + C (x, l)

Step 5: Update seed points.

Step 6: Update each pixel label using

D (x, l) = wb×B (x, l)+wi×I (x, l)

Step 7: Repeat step5-6 until pixel label is optimized.

Step 8: Connect the neighboring pixel surroundings the seed pointers.

Step 9: Apply discriminative clustering to the zones obtained above.

Step 10: Generate final segmented image Iseg with distinct colors for each segment.

Step 11: Apply Level3 2D-DWT to Iseg and the feature to f.

f→ f υ fi , Where fi is feature set from Iseg

Step 12: final feature set F is given to ADBRF classifier.

D. Classification using ADBRF

ADBRF is an acronym for AdaBoost with random forests algorithm. In this method, AdaBoost is combined with random forests algorithm for the classification of brain tissues in MR images. It is used to better the results of the accuracy and stability of the any learning algorithm. ADB combines several weak classifiers with high error rates and generate a classifier with a small training error rate [8, 9]. ADB is easy to implement, fast and simple. ADB algorithm has been successfully applied to various classification techniques as it does not require information about weak learner, has the ability to identify outliers and non-parametric in nature [10]. RF is a machine learning algorithm which is simple, effectively estimates the missing data, robust to outliers and noise [6]. It can run efficiently on large datasets, estimates important features for classification and handles thousands of input variables without attribute deletion. It is a collection of tree structured classifiers where each tree values are depended on independently sampled values of random vector and distribution of trees in the forest [18]. Here, we use this algorithm for binary classification; it results in two class labels 0 and 1. The class label 0 denotes the normal class whereas the class label 1 denotes the abnormal class. After classification, it calls a base learning algorithm (RF) for number of iterations.

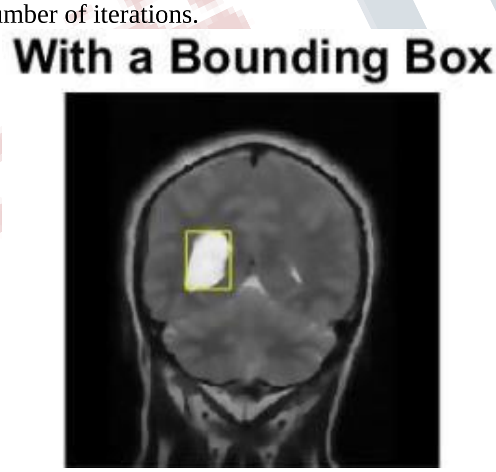

Figure.5 brain tumor detection.

IV. SIMULATION RESULTS

In this section, various brain MRI segmentation methods are evaluated their performance on two famous MRI datasets namely Internet Brain Segmentation Repository (IBSR) [14] and BrainWeb database [15]. IBSR dataset consists of 18 images, which provides their ground truth segmentation of brain tissues like GM, WM and CSF, with a size of 256 × 256 × 128 voxels which can be retrieved from https://www.nitrc.org/projects/ibsr. The number of supervoxels is set to 3000 in IBSR database. These segmentation methods are quantitatively evaluated by calculating the dice similarity coefficients (DSC), which measures the similarity between ground truth of tissues and automatic segmentation results.

Figure.6 final output.

Simulation is carried using MATLAB codes and the output figures are attached with each section separately for better understanding. Its performance is being evaluated on the BrainWeb dataset where it acquired 100% accuracy. BrainWeb database is a brain MRI database with several parameters and the images provided with tissue label for each brain tissue voxel, with a size of 181 × 217 pixels which can be retrieved from http://brainweb.bic.mni.mcgill.ca/brainweb/. In this dataset, The echo time and the repetition time have been set to 10ms and 18ms respectively.

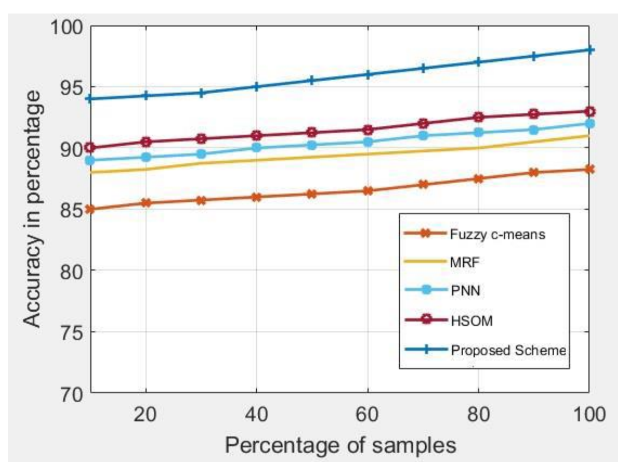

Figure.6 comparison with other state of the art methods.

A total of 200 samples are analyzed for the purpose. For computing the accuracy the k-fold (k = 5) cross-validation strategy has been adopted. Overall accuracy rate of 96% has been reported for the proposed scheme on the said dataset. This is quite satisfactory. A comparative analysis is also performed with other proposed algorithms on same problem statement. The proposed scheme outperforms the rest of the state of the art methods as shown in the above figure.

CONCLUSION

This work presents a framework for automated brain tumor detection using discriminative clustering based brain MRI segmentation. Superpixel zoning and discriminative clustering method is applied on brain MR image to partition the vital brain tissues into: White matter (WM), Grey matter (GM), and cerebro spinal fluid (CSF). This method uses a two-dimensional discrete wavelet transform (2D DWT), which generates candidate area matrix vectors. These vectors are used for feature extraction from the brain MR images. This method also uses a classification algorithm namely, AdaBoost with random forests (ADBRF) algorithm which classifies the brain MR image into normal or abnormal. The classification of the different types of brain tumors such as glioma, meningioma and cerebral toxoplasmosis etc., using novel image processing algorithms to improve diagnosis is the point of our further research.

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