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EFFICIENT GROWTH MODEL TECHNIQUES IN BAYESIAN CLASSIFICATION USING MRI IMAGES

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ABSTRACT-Identification of brain abnormalities from medical images is critical, complicated and time consuming task for a radiologist. Computer Aided Diagnostic (CAD) systems is the only solution available to reduce the burden of radiologists and medical practitioners. An ideal CAD system should identify the problem areas and compute different parameters crucial for isolating risk factors and determination of abnormalities. Magnetic Resonance Imaging for brain is considered the best imaging modality for detection of abnormality. Brain images suffer from several problems like noise partial volume effect due to overlapping tissues that needs to be addressed before segmentation. Finally, the brain has to be segmented based on key tissue regions after removal of all non-brain tissues. Tumors can be benign or malignant. Imaging plays a central role in the diagnosis and treatment planning of brain tumor. Tumor volume is an important diagnostic indicator in treatment planning and results assessment for brain tumor. The measurement of brain tumor volume could assist tumor staging for effective treatment surgical planning. Imaging of the tumors can be done by CT scan, Ultrasound and MRI etc.

CNN were used to achieve some breakthrough results and win well-known contests. The application of convolutional layers consists in convolving a signal or an image with kernels to obtain feature maps. So, a unit in a feature map is connected to the previous layer through the weights of the kernels. The weights of the kernels are adapted during the training phase by backpropagation, in order to enhance certain characteristics of the input. Since the kernels are shared among all units of the same feature maps, convolutional layers have fewer weights to train than dense FC layers, making CNN easier to train and less prone to overfitting. Moreover, since the same kernel is convolved over all the image, the same feature is detected independently of the location – translation invariance. By using kernels, information of the neighborhood is taken into account, which is an useful source of context information. Usually, a nonlinear activation function is applied on the output of each neural unit.

The region growing segmentation and support vector machine classification is preferred for its wide range of applications and automatic features. Preprocessing experiments are carried out to find which type of location bounding box will be more beneficial. This reduces the effect of the speckle and preserves the tumor edges: thereby provide the foundation for a successful segmentation. The tumor boundaries are outlined more precisely by the region growing algorithm. The extracted portion is marked automatically for ease of display. The region growing method works relatively fast and enables accurate tumor

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segmentation. The efficient method for brain tumor detection is Bayesian method.

KEYWORDS: Magnetic Resonance Imaging, Glioma, BrainTumor, Brain Tumor Segmentation, Deep Learning, Convolutional Neural Networks,Growth Model.

I.INTRODUCTION

According to the World Health Organization (WHO)

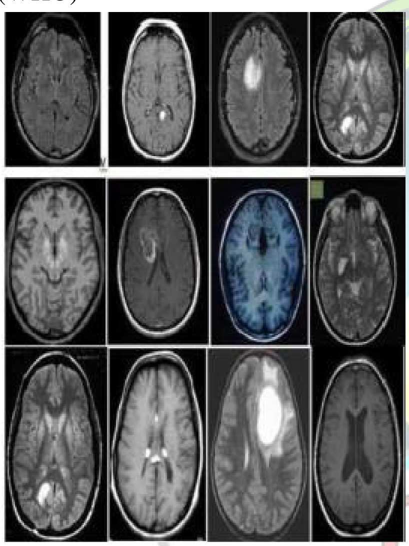

Figure 1: MRI brain Image dataset

Image processing becomes one of the important role in the field of Medical Imaging. Magnetic resonance image (MRI) becomes an important tool for most of the researcher. It produce high quantized image giving minute details regarding delegate structure within human body. The results obtained from analysis are used to guide for the treatment. Here a tumor may be defined as a swelling part of a body caused due to growth of tissue or cell. Studies have found that brain tumor is caused due to exposure to ionizing radiation such as radiation therapy where the machine is aim to the head and even caused due to family history. So it becomes important to detect tumor in early stage so as to give early treatment. This model implements patient-independent task estimates, one of the most common brain diseases is tumor and this is the reason for the diagnosis & treatment of the brain tumor have vital importance for more than 400000 persons each year in the world. The brain tumor is unnecessary growth of mass or a group of abnormal cells inside or around the brain.The brain tumor is classified in two types first one is malignant or cancerous & second is benign tumors. Malignant or cancerous tumors are classified into primary and secondary tumors. Malignant or cancerous tumor is more harmful than benign because cancerous tumor spreads rapidly by attacking on other tissues of brain progressively improving the condition causing death. The development in medical imaging techniques in recent years allows us to use these techniques in several domains of medicine like surgical planning, statistical and time series (longitudinal) analysis, computer aided pathologies diagnosis, surgical guidance. Magnetic Resonance Imaging (MRI) is the most frequently used imaging technique in neuroscience and neurosurgery for these applications. MRI helps to perfectly visualizes anatomic structures of the brain such as deep structures and tissues of the brain by creating 3D image. Some of the datasets of MRI images of brain with tumor & non-tumor is as shown in Fig.1.

MRI being an advanced medical imaging technique provides valuable information about the human soft tissue anatomy. It can provide three dimensional (3D) data depicting a high contrast between the soft tissues. Segmentation of MR images into different tissue classes such as white matter (WM), gray matter(GM) and cerebrospinal fluid (CSF) is considered as an important task. Brain MRI images possess a number of features. In addition, these images have a relatively high contrast between different tissues. Christo Ananth et al. [11] discussed about efficient content-based medical image retrieval, dignified according to the

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Patterns for Next generation Database systems (PANDA) framework for pattern representation and management. The proposed scheme use 2-D Wavelet Transform that involves block-based low-level feature extraction from images. An expectation–maximization algorithm is used to cluster the feature space to form higher level, semantically meaningful patterns. Then, the 2-component property of PANDA is exploited: the similarity between two clusters is estimated as a function of the similarity of both their structures and the measure components. Experiments were performed on a large set of reference radiographic images, using different kinds of features to encode the low-level image content. Through this experimentation, it is shown that the proposed scheme can be efficiently and effectively applied for medical image retrieval from large databases, providing unsupervised semantic interpretation of the results, which can be further extended by knowledge representation methodologies.

II.EXISTING SYSTEM

Among brain tumors, gliomas are the most common and aggressive, leading to a very short life expectancy in their highest grade. Thus, treatment planning is a key stage to improve the quality of life of oncological patients. Magnetic Resonance Imaging (MRI) is a widely used imaging technique to assess these tumors, but the large amount of data produced by MRI prevents manual segmentation in a reasonable time, limiting the use of precise quantitative measurements in the clinical practice. So, automatic and reliable segmentation methods are required; however, the large spatial and structural variability among brain tumors make automatic segmentation a challenging problem. In this paper, they discussed an automatic segmentation method based on Convolutional Neural Networks (CNN), exploring small 3_3 kernels. The use of small kernels allows designing a deeper architecture, besides having a positive effect against overfitting, given the fewer number of weights in the network. We also investigated the use of intensity normalization as a pre-processing step, which though not common in CNN-based segmentation methods, proved together with data augmentation to be very effective for brain tumor segmentation in MRI images. Our proposal was validated in the Brain Tumor Segmentation Challenge 2013 database (BRATS 2013), obtaining simultaneously the first position for the complete, core, and enhancing regions in Dice Similarity Coefficient metric (0:88, 0:83, 0:77) for the Challenge data set. Also, it obtained the overall first position by the online evaluation platform. We also participated in the on-site BRATS 2015 Challenge using the same model, obtaining the second place, with Dice Similarity Coefficient metric of 0:78, 0:65, and 0:75 for the complete, core, and enhancing regions, respectively.

III.PROPOSED SYSTEM

In existing system the technique used was Convolutional Neural Networks(CNN),in our project we proposed using Bayesian Classifier as discussed below.

Bayesian Classifier:

Bayes Theorem

Bayesian theory gives a mathematical calculus of degree of belief. Bayes theorem is a way to calculate the conditional probabilities of features. Bayes theorem can be defined as

• Let X is a data sample/Object.

• Let H be some hypothesis, such as X belongs to a specified class C.

• P (H) is known as the prior probability. P (H) tells the probability of given
data sample belonging to the specified class.

• P (X|H) is the probability that the hypothesis H holds given the observed data
sample/object X.

• P (H|X) is called the posterior probability. It is based on more informationthan the prior probability P (H), which is independent of X.

Baye's Theorem provides a way of calculating the posterior probability

P(H|X) =P(X|H)P(H) / P(X) (1)

P (X|H) is the posterior probability of X conditioned on H. P(X) is the prior probability of X. Posterior probabilities are class density estimates. Accuracy of the classifier strongly depends upon this parameter. As much accurate the class density estimates much higher accuracy is achieved.

Naïve Bayes Classification:

Bayesian classifier estimates the class of unknown data item using probabilistic statistics model. Challenge in the Bayesian classification is to determine the class of data sample which have some number of attributes. Bayesian classification estimates the class of this unknown data item on the basis of known data item which are provided with the class labels for the training purpose of the Bayesian classification. Let S be the dataset with t objects such that X1, X2,…,Xt . Each object have n attributes such that A1, A2,...,An. let there are m classes C1,C2,…,Cm. Naïve bayes classifier predicted the unknown data sample X which is without the label to the class Ci if and only if P(Ci|X)>P(Cj|X) for $1\leq j \leq m$, $j \neq i$ (4) then X is assigned to Ci. This is called Bayes decision rule. Using Bayes theorem maximum posterior hypothesis can be calculated using

$$P(C_i)|X) = P(X|C_i)P(C_i)/P(X) \qquad (2)$$

The class prior probabilities P (Ci) can be estimated by Bayesian Classification Using DCT Features for Brain Tumor Detection.

$$P(Ci)=si/s \qquad (3)$$

Where si is the total number of training samples which have class Ci and s is the total number of training samples. In order to reduce a computation and to avoid the effect of scarcity of data the naïve assumption of class conditional independence is made. The probabilities P (x1|Ci), P (x2|Ci), …, P (xn|Ci) are estimated from the training samples. An attribute Ak can take on the values x1k, x2k,..

$$P(x_k|C_i)=s_{ik}/s_i \qquad (4)$$

Where s_{ik} is the number of training samples of class C_i having the value x_k for A_k and s_i is the number of training samples belonging to Ci In Naïve bayes classification dataset is divided into two sets, training and testing respectively. Training dataset is considered as prior information and model is constructed on the basis of this training dataset. Class of the unknown data is determined using this model.

The listed below are some of the methods;

A. Region-*growing*

In this technique the images are partitioned by organizing the nearest pixel of similar kind.It starts with a pixel (initial seed) that having similar properties. Accordingly the neighbouring pixels based on homogeneity criteria are appended progressively to the seed. In splitting process,region get devided into subregions that does'nt satify a given homogeneity crieteria.Spliting and merging can be used together and its performance mostly depends on the selected homogeneity criterion. Without tuning homogeneity parameters, the seeded region growing technique is controlled by a number of initial seeds. If the number of regions was approximately known & used it to estimate the corresponding parameters of edge detection.

B. Clustering

The method of clustering organizes the objects into groups based on some feature, attribute and characteristic. Hence a cluster consists of groups of similar objects. There are two types of clustering, supervised and unsupervised. In supervised type

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clustering, cluster criteria are specified by the user. In unsupervised type, the cluster criteria are decided by the clustering system itself. Image/Symmetry Analysis is an interactive segmentation method that in addition to area of the region and edge information uses prior information, also its symmetry analysis which is more consistent in pathological cases. A conceptually easy supervised block-based, shape, texture; content based technique has been used to analyze MRI brain images with relatively lower computational requirements. Classifying regions by means of their multiparameter values does the study of the regions of physiological and pathological interest easier and more definable.

Segmentation Method	Advantages	Disadvantages
Region Based growing	Simple and capable of correctly segmenting regions that have similar properties and generating connected regions.	Partial volume effect. Noise or variation of intensity may result in holes or over segmentation.
Clustering	Unsupervised.Always converges the boundary of tumor.	Long Computational

IV. CONCLUSION

MRI images are more useful & provide much better result about soft tissues of human brain compared to computerized tomography (CT) images. MRI images help to brain tumor detection by accurate segmentation which is very crucial otherwise the wrong identification of disease can lead to several consequences. Accuracy and reliability are always assigned much importance in tumor diagnosis as it is complex process.

Image segmentation is active research field for the last several decades. Moreover, it is a most challenging and active research field in the medical image processing. Image segmentation is the preliminary stage of almost all image analyzing tools. There exist variety of image segmentation methods and good prior knowledge for brain MRI segmentation. But still, brain MRI segmentation is a challenging task and there is a need for future research to improve the accuracy, precision and speed of segmentation methods. Using improved atlas based methods parallelization and combining different methods can be the way for making improvement in brain segmentation methods.

V. FUTURE ASPECTS

The future work regarding brain tumor segmentation should focus on improving the accuracy by using additional features such as prior knowledge, shape and models. To achieve better prediction rate, gradient with HPF (high pass filtering) can be used as it prominently give us edges with higher accuracy.

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