Brain Region Segmentation using CNN

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Abstract
An important problem in medical image analysis is the segmentation of anatomical regions of interest. Once regions of interest are segmented, helps radiologists extract shape, appearance and other structural features that can be analyzed for disease diagnosis or treatment evaluation. Many segmentation techniques such as mean shift, region growing, water shed, graph cuts, fuzzy connectivity etc. are available for medical imaging especially for brain MRI. In our work, a fully automated system for brain region segmentation by using Human intelligence based deep learning technique is proposed. Deep learning technique is most popular state of the art method in recent applications. There are two stages pre-processing and segmentation via Convolutional Neural Network CNN.The MRI image with noise is used as an input image. MRI images are collected from publicly available database Open Access Series of Image Studies (OASIS). Three layers are used in this network, which is used to segment the brain region.

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I. INTRODUCTION

Cancer can be defined as the uncontrolled, unnatural growth and division of the cells in the body. Occurrence, as a mass, of these unnatural cell growth and division in the brain tissue is called a brain tumor. While brain tumors are not very common, they are one of the most lethal cancers.

Depending on their initial origin, brain tumors can be considered as either primary brain tumors or metastatic brain tumors. In primary ones, the origin of the cells are brain tissue cells, where in metastatic ones cells become cancerous at any other part of the body and spread into the brain. Gliomas are type of brain tumors that originate from glial cells. They are the main type of brain tumors that current brain tumor segmentation research focuses on. The term glioma is a general term that is used to describe different types of glioma ranging from low-grade Gliomas like astrocytomas and oligodendrogliomas.

To the high grade (grade IV) glioblastoma multiform (GBM), which is the most aggressive and the most common primary malignant brain tumor2. Surgery, chemotherapy and radiotherapy are the techniques used, usually in combination, to treat gliomas3.

Early diagnosis of glioma plays an important role in improving treatment possibilities. Medical Imaging techniques such as Computed Tomography (CT), Single-Photon Emission Computed Tomography (SPECT), Positron Emission Tomography (PET), Magnetic Resonance

Spectroscopy (MRS) and Magnetic Resonance Imaging (MRI) are all used to provide valuable information about shape, size, location and metabolism of brain tumors assisting in diagnosis. While these modalities are used in combination to provide the highest detailed information about the brain tumors, due to its good soft tissue contrast and widely availability MRI is considered as the standard technique. MRI is a non-invasive in vivo imaging technique that uses radio frequency signals to excite target tissues to produce their internal images under the influence of a very powerful magnetic field. Images of different MRI sequences are generated by altering excitation and repetition times during image acquisition. These different MRI modalities produce different types of tissue contrast images, thus providing valuable structural information and enabling diagnosis and segmentation of tumors along with their subregions4. Four standard MRI modalities used for glioma diagnosis include T1-weighted MRI (T1), T2-weighted MRI (T2), T1-weighted MRI with gadolinium contrast enhancement (T1-Gd) and Fluid Attenuated Inversion Recovery (FLAIR). During MRI acquisition, although can vary from device to device, around one hundred and fifty slices of 2D images are produced to represent the 3D brain volume. Furthermore, when the slices from the required standard modalities are combined for diagnosis the data becomes very populated and complicated.

Accurate diagnosis in medical procedure has attained using different imaging modalities such as Magnetic Resonance (MR) imaging, Computed Tomography (CT), digital mammography etc. These can provide very detailed and informative anatomy of a subject. According to these developments, diagnosis imaging became an important tool in diagnosis and planning treatment. Brain region segmentation is important first step in every neuroimaging applications such as tissues segmentation and volume calculation. Automatic skull removal is extremely difficult time consuming process because of complex boundaries and low contrast. Research community develops many methods.

Deep learning, otherwise called as deep structured learning is one of the machine learning algorithms. It learns data from the input image using either supervised or unsupervised. In this paper, supervised learning approach using Convolutional Neural Network is used for accurate brain region segmentation.

II. Literature Work.

Many methods have been developed to segment brain regions. Mainly he has two obstacles to noise and intensity uniformity. Therefore, before further analysis of the image, denoising should be performed [1]. A non-local mean filter algorithm was developed to remove Rician noise [2]. We use the new similarity to remove Rician noise based on this pixel value [3]. A 3D Convolutional Neural Network is used for the brain region segmentation process [4]. A fully collapsed network is trained in two ways. One for patch-wise prediction and one for supervised pre-training [5]. Mohammad Hava ei et al [6] proposed his CNN. It is different from image processing technology. Use both local and global context functions at the same time. This document describes a two-phase training process. Tumor labeling is easy to predict. This speeds up 30 times faster than prior art methods. Deep learning method provides accurate results. This method is more efficient and evaluates large amounts of data in MRI images [7]. Brain tumor segmentation primarily focuses on network architecture and learns complex features from the data itself.It is based on both discriminative and generative models. The discrimination method learns and mainly relies on the correlation between the input image and the ground truth image.About feature extraction. Generative models are used to extract tumor cells. A 3D CNN architecture is used for the multimodal glioma segmentation task [8]. Cubes of voxels and patches are extracted from the MRI image and used as input to the method. In this article, we use CNN to predict tissue labels from voxel cubes. A 3D Convolutional Neural Network (CNN) proposed by Konstantins Kamnitsas [9] is used for accurate segmentation of brain lesions. Input images are processed simultaneously at multiple scales using a dual-path architecture. Local and contextual information considered and estimated for each neighborhood i. H. voxels by classifying each voxel in the imagesensible way. This is achieved by using sequential convolution of the input to the cascade network, which reduces the false positive rate. Deep CNN uses small convolution kernels for glioma segmentation [10]. Use smaller kernels for more powerful convolutional layers while having the same receptive field as larger kernels. It has two cascaded 3 × 3 layer convolutions with the same effective receptive field as the 5 × 5 layers, but with smaller weights. one of the advantages of using this method is designed to reduce overfitting, since smaller kernels carry less weight than larger kernels. Olaf Ronneberger [11] proposed convolutional networks for biomedical image segmentation. This architecture consists of a contracting path and a symmetrically expanding path. The contraction pass is used to capture context and the expansion pass is used for precise localization.

III. Implementation

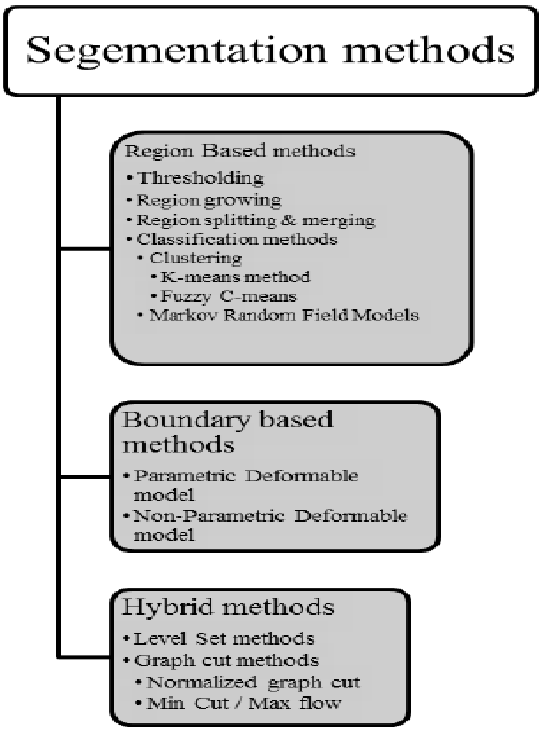

Figure1: Segmentation Methods

TABLE I.RESULTS FOR DENOISED IMAGE AND BRAIN REGION SEGMENTATION IMAGES

INPUT IMAGES	DENOISED IMAGE PSNR (DB)	MSE	ACCURACY (%)	SENSITIVITY (%)	SPECIFICITY (%)
IMAGE 1	43.39	1.3610	0.9635	0.9545	0.9677
IMAGE 2	43.42	1.3443	0.9678	09586	0.9723
IMAGE 3	43.50	1.2922	0.9468	0.8348	0.9968
IMAGE 4	43.49	1.3004	0.9436	0.8473	0.9884

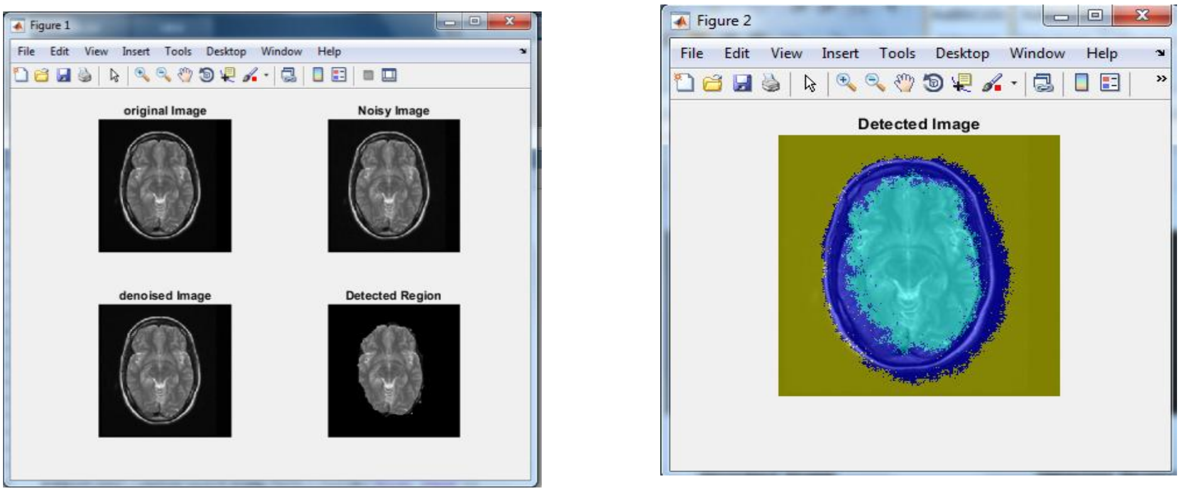

Figure2: Simulation Results

TABLE II:
RESULTS FOR DENOISED IMAGE AND BRAIN REGION SEGMENTATION IMAGES with SI, CDR,USE,OSE,TSE

INPUT IMAGES	DENOISED IMAGE PSNR (DB)	MSE	ACC (%)	SE (%)	SPE (%)	SI	CDR	USE	OSE	TSE
Image1	43.39	1.361	0.9635	0.9545	0.9677	0.9433	0.9545	0.0693	0.0455	0.1148
Image2	43.42	1.344	0.9678	0.9586	0.9723	0.9513	0.9586	0.0569	0.0414	0.0982
Image3	43.50	1.292	0.9468	0.8348	0.9968	0.9064	0.8348	0.0072	0.1652	0.1724
Image4	43.49	1.300	0.9468	0.8473	0.9884	0.9051	0.8473	0.0248	0.1527	0.1776

IV. Conclusion

In this work, a convolutional neural network (CNN) is used for the mind segmentation. This work uses a freely accessible MRI database called OASIS. The MRI images are first prepared for him to emit Rice's screams using the NLM (Non Local Mean) channel, and the non-mental tissue (cranial compartment) is drained using the CNN. One of the advantages of CNN is that it does not require high quality highlights. It's legally referring to the photo. Running CNN gives high accuracy in the range of 94% to 96%. In future work, typical Black & White issues, dark issues, and cerebrospinal fluid can be fragmented using computational insight methods. Given the change in volume of these tissues, we can distinguish scattering in the cerebrum.

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