AUTOMATED BRAIN TUMOR SEGMENTATION AND CLASSIFICATION USING CONVOLUTIONAL NEURALNETWORK IN MR IMAGES

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Abstract- Magnetic Resonance Imaging (MRI) is a widely used imaging technique to assess these tumors. The large amount of data produced by MRI prevents manual segmentation in a reasonable time. Automatic and reliable segmentation methods are required. Independent projection-based classification (LIPC) is used to segment the tumor region. Here, 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. Here, proposed an automatic segmentation method based on Convolutional Neural Networks (CNN), exploring small 3x3 kernels. The use of small kernels allows designing a deeper architecture, besides having a positive effect against over fitting, given the fewer number of weights in the network. Results reported on public benchmarks reveal that our architecture achieves competitive accuracy compared to the state-of-the-art brain tumor segmentation methods while being computationally efficient..

***Index Terms*—Digital Image Processing,Positron Emission Tomography,PhotomultiplierTube,ComputedTomography,Magnetic Resonance Image,Fluid-Attenuated Inversion Recovery ,Single Photon Emission Computed Tomography TR Repetition Time, echo time ,Region of Interest.**

I. INTRODUCTION

A. General

Gliomas are the most frequent primary brain tumors in adults that cause severe damage to the central nervous system. The less aggressive forms of the disease (i.e. low grade) in the clinical population come with a life expectancy of several years, while the more aggressive variants (i.e. high grade) come with a life expectancy of at most two years. For both groups, magnetic resonance imaging (MRI) can provide detailed images of the brain, and is one of the most common neuroimaging protocols used before and after treatment to reveal clues about the disease characteristics. Accurate segmentation of brain tumors from MR images would be of enormous potential value for improved diagnosis, growth rate prediction and treatment planning.

However, automated and accurate brain tumor segmentation in multimodal MRI volumes is technically challenging due to several reasons. First, the tumor areas are only defined through image intensity profiles that often overlap with adjacent normal tissue due to partial voluming or bias field artifacts. Furthermore, tumors can appear anywhere in the brain, with varying shapes and sizes. Finally, in order to capture rich biological information and better segment each sub-component in brain tumors, it is important to conduct studies on multimodal MRI volumes, e.g. T1, T1c, T2, and FLAIR, to map a unique label to each tissue type. It thus somewhat complicates the information processing tasks.

In the past several years, a wealth of techniques were devoted to automated brain tumor segmentation, in meeting the variety of needs of clinical diagnosing and therapy, including generative models based approaches and discriminative models based approaches. Generative probabilistic models make use of domain-specific prior knowledge about the anatomy and appearance of the different tissue types. They usually model brain tumors as outliers relative to the shape or image signal of normal (or average) brains. Transforming the semantic interpretations of the tumor sub-components in the image into appropriate probabilistic models, however, is difficult. Discriminative modeling approaches, on the other hand, exploit little domain knowledge on the brain's anatomy and instead directly learn the relationship between low level image features and segmentation labels. Typical discriminative models have a common implementation of a conventional machine learning pipeline relying on dense, voxel-wise features and classification algorithms such as SVMs and decision forests. A thorough review of different algorithms for brain tumor segmentation can be found. In the following, we briefly review several representative types of segmentation methods that are closely related with ours.

Random forest (RF) is one of the most successful supervised voxel-wise classifiers that enjoys sustained attention in the medical image segmentation. The random forests are inherently suited for handling a high number of multi-class data with high data dimension, and the methods relying on RFs are among the most accurate for many brain tissue segmentation tasks. Representative work is that Wang et al. proposed a multi-source integration framework based on random forest technique to effectively integrate features from multi-source images together for infant brain tissue segmentation. Tustison et al. introduced a supervised whole-brain and tumor segmentation approach by using multiple modality intensity, geometry, and asymmetry feature sets in a random forests framework. Zikic et al. proposed a method for multi-atlas label propagation based on encoding the individual atlases by randomized classification forests. Peter et al. showed that by using ensembles of random forests facilitated with deep neural network features can achieve better performance than simply using deep neural networks. Although those methods have achieved very successful results, they remain to depend on the computation of a large number of handcrafted features that exploit very generic edge-related information instead of brain tumor specific information. Furthermore, the typical RF outputs are not geometrically constrained.

MAGNETIC RESONANCE IMAGING (MRI) OF BRAIN TUMORS

Brain cancer can be counted among the most deadly and intractable diseases. Tumors may be embedded in regions of the brain that are critical to orchestrating the body's vital functions, while they shed cells to invade other parts of the brain, forming more tumors too small to detect using conventional imaging techniques. Brain cancer's location and ability to spread quickly makes treatment with surgery or radiation like fighting an enemy hiding out among minefields and caves. In recent years, the occurrence of brain tumors has been on the rise. Unfortunately, many of these tumors will be detected too late, after symptoms appear. The past few years had witnessed a rapid and multi directional increase in the applications of image processing. In today's digital era, capturing, storing and analysis of medical images had been digitized.

Illustration of a brain tumor

The challenge stands tall especially in regions with abnormal color and shape which needs to be identified by radiologists for future studies. The key task in designing such image processing and computer vision applications is the accurate segmentation of medical images. Image segmentation is the process of partitioning different regions of the image based on different criteria. Surgical planning, post-surgical assessment, abnormality detection, and many other medical applications require medical image segmentation.

Brain image segmentation from MRI images is complicated and challenging but its precise and exact segmentation is necessary for tumors detection and their classification, edema, hemorrhage detection and necrotic tissues. For early detection of abnormalities in brain parts, MRI imaging is the most efficient imaging technique.
The morphological operations are basically applied on some assumptions about the size and shape of the tumor and in the end the tumor is mapped onto the original gray scale image with 255 intensity to make visible the tumor in the image.

For the treatment of patients with brain tumors, imaging of the brain is often indicated at different stages and usually has a significant role in each of them. Several stages of management may be considered:

· Detection or confirmation that a structural abnormality is present, · Localization and assessment of the extent of any abnormality, · Characterization of the abnormality, · Assessment of the nature of a tumor, · Facilitation of additional diagnosis procedures, and planning for surgery or other types of therapy, Intra-operative control of rejection progress, Monitoring of response to therapy.

A variety of imaging techniques are used to study brain tumors, including computed tomography (CT), magnetic resonance (MR) imaging, and single photon emission computed tomography (SPECT) imaging, positron emission tomography (PET) scanning, and cerebral angiography. At this moment, CT and MR imaging are the most widely used techniques, because of their widespread availability and their ability to produce high resolution images of normal anatomic structures and pathological tissues.

CT is the fastest modality, making it the preferred examination for imaging critically ill or medically unstable patients. SPECT and PET imaging serve smaller roles, although their ability to provide information on tissue biology and Physiology can be greatly helpful. PET scanning is also used to evaluate tumor grade.

MRI Modalities

The variable behavior of protons within different tissues leads to differences in tissue appearance. The amount of signal produced by specific tissue types is determined by their number of mobile hydrogen protons, the speed at which they are moving, and the tissue's T1 and T2 relaxation times. As T1 and T2 relaxation times are time dependent, the timing of the RF pulse and the reading of the radiated RF energy change the appearance of the image. The repetition time (TR) describes the time between successive applications of RF pulse sequences. The echo time (TE) describes the delay before the RF energy radiated by the tissue in question is measured.

The pulse sequence, which is described by the TR and TE and indicates the technique used to administer the RF energy, can be chosen to maximize the effect of differences in T1 or T2. This gives rise to the description of an MRI image as T1or T2 weighted. The standard MRI pulse sequence for anatomic and pathologic detail is a spin echo sequence. T1-weighted images (short TR, short TE) provide better anatomic detail, while T2 weighted images (long TR, long TE), which are more sensitive to water content, are more sensitive to pathology. The intermediate or proton density images (long TR, short TE) provide improved contrast between lesions and cerebrospinal fluid.

Fluid-attenuated inversion recovery (FLAIR) image is another pulse sequence that is useful in detecting low contrast lesions. With FLAIR (long T1, long TR, and variable TE), the CSF signal is nulled, enabling pathology adjacent to the CSF to be seen more clearly, i.e. FLAIR sequence produces heavily T2- weighted and CSF-nulled MR image. Many reports confirm the superiority of the FLAIR sequence over conventional spin-echo (SE) sequences with respect to disease. This technique has assumed an important role in routine brain imaging because of its presumed ability to enhance the visibility of brain lesions compared with that of proton density weighted and of T2-weighted spin-echo sequences. FLAIR images increase detection accuracy for cortical, subcortical and periventricular lesions, and allow more efficient review, compared with T2-weighted images. In FLAIR images, edema is often delineated from tumor, and CSF is distinguished from a cystic or necrotic component, better than T2-weighted and proton density-weighted images.

In brain tumors, T1 is proportional to edema. However, a change in oxygen partial pressure is sufficient to alter T1 significantly; hence T1-weighted imaging will not bead equate for accurate quantification of tumor edema. The findings on T2-weighted (also FLAIR) MR images also correlate directly with extracellular water volume and total water content, and inversely with intracellular water content in several tumors. Therefore T2-weighted (also FLAIR) MR images are actually imaging edema. Paramagnetic contrast agents, such as gadolinium, may be administered during MRI acquisitions to highlight regions of abnormality. After injection, the gadolinium remains in the vascular system of the brain, except where the blood-brain barrier has been interrupted. A variety of processes can disrupt the blood-brain barrier, ranging from head trauma to brain tumors.

Certain structures within the brain, such as the pituitary gland, pineal gland, pituitary infundibulum, choroids plexus, and veins in which the blood-brain barrier is not intact, normally display contrast enhancement. Thus, contrast enhanced T1-weighted (CE-T1w) images provide anatomic details of the brain and distinguish tumor from edema.

MRI is evolving rapidly and newer imaging sequences, such as echo planar MRI, are being developed, reducing scan times and improving the information obtained from the images. Echo planar MRI can scan images in less than 100 milliseconds and provides information on tumor diffusion and perfusion. Diffusion weighted MR imaging permits the assessment of the mobility of water molecules and may be useful in helping to distinguish tumor from edema, cystic changes, and normal white matter.

TUMOR

A tumor or tumor is the name for a neoplasm or a solid lesion formed by an abnormal growth of cells (termed neoplastic) which looks like a swelling. Tumor is not synonymous with cancer. A tumor can be benign, pre-malignant or malignant, whereas cancer is by definition malignant.

TYPES OF TUMOR

Benign Tumor

A benign tumor is a tumor that lacks all three of the malignant properties of a cancer. Thus, by definition, a benign tumor does not grow in an unlimited, aggressive manner, does not invade surrounding tissues, and does not spread to non-adjacent tissues. Common examples of benign tumors include moles and uterine fibroid.

Malignant

Malignancy is the tendency of a medical condition, especially tumors, to become progressively worse and to potentially result in death. It is characterized by the properties of anaplasia, invasiveness, and metastasis. Malignant is a corresponding adjectival medical term used to describe a severe and progressively worsening disease. The term is most familiar as a description of cancer.

Premalignant

A precancerous condition (or premalignant condition) is a disease, syndrome, or finding that, if left untreated, may lead to cancer. It is a generalized state associated with a significantly increased risk of cancer.

BRAIN TUMOR SEGMENTATION The most important aim of medical image analysis in general, and brain magnetic resonance image (MRI) analysis in particular, is to extract clinical information that would improve diagnosis and treatment of disease. Brain tumors are one of the most common brain diseases, so detection and segmentation of brain tumors in MRI are important in medical diagnosis. The aim is to provide information associated with anatomical structures as well as potential abnormal tissues necessary to treatment planning and patient follow-up. The segmentation of brain tumors can also be helpful for general modeling of pathological brains and the construction of pathological brain atlases.

Conventionally, simple thresholding or morphological techniques have been used on each image to segment the tissue or region of interest for diagnosis, treatment planning, and follow-up of the patients. These methods are unable to exploit all information provided by MRI. Advanced image analysis techniques have been and still are being developed to optimally use MRI data and solve the problems associated with previous techniques. Most of the methods presented for tumor detection and segmentation have used several techniques and we cannot make a clear division between them but in general, as classically done in image segmentation, we can divide the methods into three groups:

- Region based method
- Contour based method
- Fusion of region and boundary based method

Region Based Method

Region based methods seek out clusters of voxels that share some measure of similarity. These methods reduce operator interaction by automating some aspects of applying the low level operations, such as threshold selection, histogram analysis, classification. They can be supervised or non-supervised. In region-based methods, an algorithm usually searches for connected regions of pixels/n voxels with some similar features such as brightness, texture pattern, etc.

Thresholding, region growing and classification are the famous algorithms of this type. In recent years, researchers have developed advanced and mixed region based methods for tumor detection and segmentation.

Here we further classify region-based methods into the following categories: (1) classification-based

(2) clustering-based

(3) morphology-based

(4) atlas-based

(5) prior knowledge-based

(6) texture-based

(7) feature extraction-based

(8) fusion-based

(9) neural network-based

(10) fuzzy-based and

(11) fractal-based method

In clinical applications, all of the tumor components are important for diagnosis, treatment and follow-up. In order to segment accurately all parts of the tumor, it is necessary to use T1-weighted or contrast enhanced T1-weighted images with FLAIR or T2-weighted images. The automation level in these methods is relatively high but in some of the methods the user interaction is needed.

The main problem of these methods is the quality of the segmentation in the border of tumors. Due to the partial volume effect the region-based techniques suffer from misclassification of voxels and hence, it is difficult to have a crisp region of tumor.

Another problem is the segmentation of heterogeneous tumors and it remains an unsolved problem in these methods.

Boundary Based Method

In order to overcome some of the limitations of region-based methods for segmentation, boundary-based methods are used to look for explicit or implicit boundaries between regions corresponding to different tissue types. In this method an algorithm searches for pixels/voxels with high gradient values that are usually edge pixels/voxels and then tries to connect them to produce a curve which represents a boundary of the object.

In the recent years deformable models, one of the most popular boundary based methods, have been widely used in image segmentation. The idea behind deformable models is quite simple. The user determines an initial guess for the contour, which is then deformed by image driven forces to the boundaries of the desired objects. In these models, two types of forces are considered. The internal forces, defined within the curve, are designed to keep the model smooth during the deformation process. These methods can also be supervised or non-supervised. They can be further classified into two classes:

(1) Parametric deformable model (classical snake) (2) Geometric deformable model (level sets)

Fusion of Region with Boundary Based Method The third core class of tumor segmentation methods is the fusion of region with boundary based methods. This class has been the most successful, as this technique uses information from two different sources: region and boundary. Due to its large success, it has recently received much attention. Looking at the advantages of boundary-based and region-based methods, the third class of brain tumor segmentation approaches was designed, which is the fusion of region with boundary based techniques. This class has been the most successful, as this technique uses information from two different sources: boundary and region. These methods take advantage of the local and global shape information for deforming the boundaries to capture the topology of tumor areas in the parametric or geometric deformable models.

CATEGORIES OF IMAGE FUSION

Image Fusion can be categorised, as multiview fusion, multifocus fusion, multitemporal fusion and multimodal fusion. Multimodal and multi temporal image fusion methods are widely used in medical image analysis.

Multimodal Fusion

Medical images are of different modalities such as: PET, CT, MRI, ultraviolet, etc. These images are fused together to get better quality single image with more and more complimentary information using multimodal image fusion. Its aim is to fuse these images to get better quality output image with maximum information from both the images. Image Fusion has majorly three steps such as image acquisition, image registration and then image fusion.

Image acquisition

Multimodal images are acquired by medical instruments such as X-ray, CT, MRI, PET etc. These instruments capture images using different radio frequencies, which limits there penetration level. Because of this the doctors depend on several instruments. One can obtain several images of the same organ using these instruments. These several images carry different information.

Image registration

Image registration, which brings the input images to spatial alignment, and combining the image functions (intensities, colors, etc). It works usually in four steps such as i) Feature detection ii) Feature matching iii) Transform model estimation and iv) Image re-sampling and transformation. Images to be considered for registration should be of equal size. Superposition based registered images of CT and MRI are considered for this implementation of image fusion.

Image Fusion

In practice, the fusion process can be carried out on data and images at four different levels such as signal, pixel, feature and decision level. Multi modal images can be very well fused using Pixel level image fusion methods.

Pixel-level image fusion means fusion at the lowest processing level referring to the merging of measured physical parameters. It generates a fused image in which each pixel is determined from a set of pixels of various images, and serves to increase the useful information content of an image. This can be carried out by selecting minimum, maximum or average of inputs.

Pixel Level Image fusion methods can be broadly classified into two that is spatial domain fusion and frequency domain fusion.

Averaging, Brovey method, SVR, IHS & Principal Component Analysis (PCA), are spatial domain methods. Gaussian, Laplacian Pyramid. Ratio-of-lowpass Pyramid, Gradient Pyramid, FSD Pyramid and Morphological Pyramid and Discrete Wavelet based methods etc. are of frequency domain.

DIGITAL IMAGE PROCESSING

The processing of a 2 D image by a digital computer is known as Digital Image Processing (DIP). Vision is a complicated process that requires numerous components of the human eye and brain to work together. The sense of vision has been one of the most vital senses for human survival and evolution. Humans use the visual system to see or acquire visual information and perceive that is the process to understand it and then deduce inferences from the perceived information. The field image processing focuses on automating the Process of gathering and processing visual information. The process of analyzing visual information by digital computer is called digital image processing. The field of digital image processing refers to processing digital images by means of a digital computer.

A digital image is composed of a finite number of elements, each of which has a particular location and value. These elements are referred to as picture elements, image elements, and pixels. Pixel is the term most widely used to denote the elements of a digital image. Vision is the most advanced of our senses, so it is not surprising that images play the single most important role in human perception.

However, unlike humans, who are limited to the visual band of the electromagnetic spectrum, imaging machines cover almost the entire EM spectrum, ranging from gamma to radio waves. They can operate on images generated by sources that humans are not accustomed to associating with images. These include ultrasound, electron microscopy, and computer generated images. Thus digital image processing encompasses a wide and varied field of applications. An image may be described as a two-dimensional function $I = f(x, y)$

Where and are spatial coordinates. Amplitude of at any pair of coordinates is called intensity or gray value of the image. When spatial coordinates and amplitude values are all finite, discrete quantities, the image is called digital image.

Digital image processing may be classified into various sub branches based on methods whose input and output are images and inputs may be images whereas outputs are attributes extracted from those images.

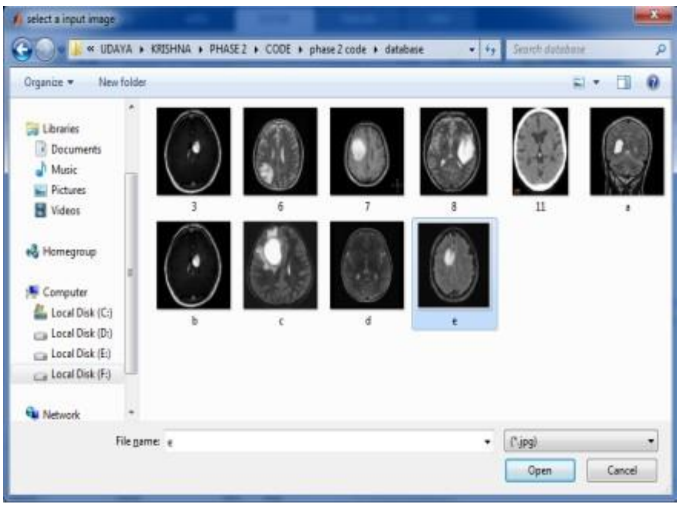
APPLICATIONS

Image Processing is used in various applications such as:

Remote Sensing ,Medical Imaging ,Textiles ,Material Science ,Military,Film industry ,Graphic arts , Printing Industry, etc.

RESULTS AND DISCUSSIONS

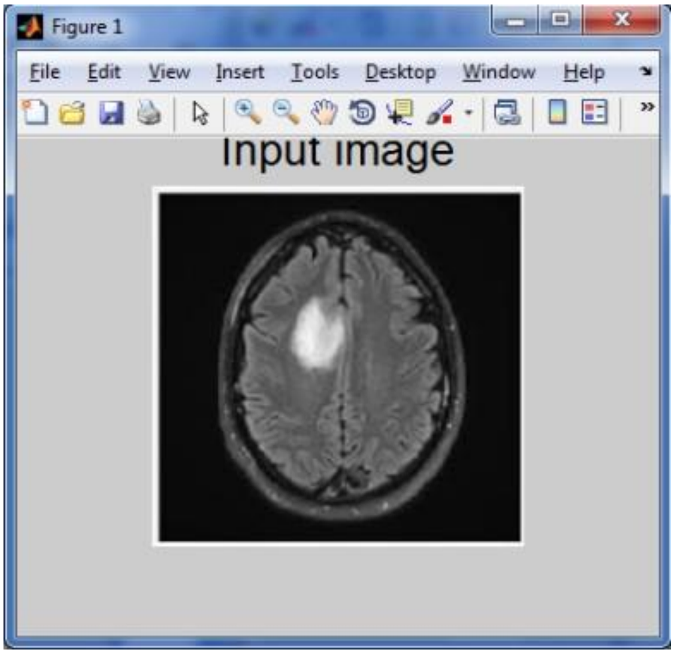
INPUT IMAGE DATASET



Input Image Dataset

The above figure represents the input image dataset. The input image is brain MRI image is a gray scale format with the various dimension size. The above datasets are collects from BRATS (Brain Tumor Segmentation) database.

INPUT IMAGE

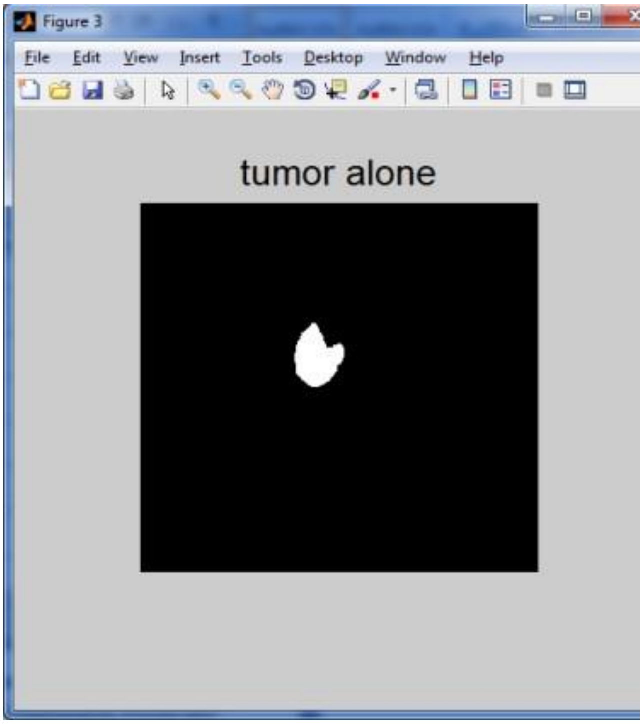


The above figure shows that the input image of the automated Brain Tumor Segmentation of MR Images. The input image is brain MRI image is a gray scale format with the dimension size of 256 x 256 pixels

FILTERED IMAGE

The above figure represents the filter image. Anisotropic diffusion filter is used in this process.

TUMOR ALONE



The above figure represents the tumor alone part. The black region represents the value as zero and white region represent as one.

CONCLUSION AND FUTURE WORK

CONCLUSION

Thus, concluded that Magnetic Resonance Imaging (MRI) is a widely used imaging technique to assess these tumors. The large amount of data produced by MRI prevents manual segmentation in a reasonable time. Automatic and reliable segmentation methods are required. Propose an automatic segmentation method based on Convolution Neural Networks (CNN), exploring small 3x3 kernels. Independent projection-based classification (LIPC) is used to segment the tumor region. Investigated the use of intensity normalization as a pre-processing CNN

based segmentation methods, proved together with data to be very effective for brain tumor segmentation in MRI images. Results reported on public benchmarks reveal that our architecture achieves competitive accuracy compared to the state-of-the-art brain tumor segmentation methods while being computationallyefficient.

FUTURE WORK

Furthermore to improve the recognition rate and classification accuracy in brain image processing. In order to use the multi layer detection process to solve the problem.

REFERENCES

1. D. Zikic, B. Glocker, and A. Criminisi, "Encoding atlases by randomized classification forests for efficient multi-atlas label propagation," Med Image Anal, vol. 18, pp. 1262-1273, 2014.

2. K. Wang and C. Ma, "A robust statistics driven volume-scalable active contour for segmenting anatomical structures in volumetric medical images with complex conditions," BioMedical Engineering OnLine, vol. 15, p. 39, 2016.

3. K. Zhang, L. Zhang, K. M. Lam, and D. Zhang, "A Level Set Approach to Image Segmentation With Intensity Inhomogeneity," Cybernetics, IEEE Transactions on vol. 46, pp. 546 - 557, 2015.

4. L. Breiman, "Random Forests," Machine Learning, vol. 45, pp.
5-32, 2001. 5. L. Wang, Y. Gao, F. Shi, G. Li, J. Gilmore, W. Lin, et al., "LINKS: learning based multi-source IntegratioN frameworK
for Segmentation of infant brain images," Neuroimage, vol. 108,pp. 160-72, Mar 2015.

6. L. Wang, Y. Gao, F. Shi, G. Li, J. Gilmore, W. Lin, et al., "Segmentation of neonatal brain MR images using patch-driven level sets," Neuroimage, vol. 84, pp. 141-158, Jan 1 2014.

7. M. Kass, A. Witkin, and D. Terzopoulos, "Snakes: Active Contour Models," International Journal of Computer Vision, vol. 1, pp. 321-331, 1988. 8. M.
Prastawa, E. Bullitt, S. Ho, and G. Gerig, "A brain tumor segmentation framework based on outlier detection," Med Image Anal., vol. 8, pp. 275-283, 2004.

9. Menze BH, Jakab A, Bauer S, Kalpathy-Cramer J, Farahani K, Kirby J, et al., "The Multimodal Brain Tumor Image Segmentation Benchmark (BRATS)," Medical
Imaging, IEEE Transactions on, vol. 34, pp. 1993-2024, Dec 4 2015.

10. Nicholas J. Tustison, K. L. Shrinidhi, MaxWintermark, Christopher R. Durst, Benjamin M. Kandel, James C. Gee, et al., "Optimal Symmetric Multimodal Templates and Concatenated Random Forests for Supervised Brain Tumor Segmentation (Simplified) with ANTsR," Neuroinformatics, vol. 13, pp. 209-25, Apr 2015.

11.P. Kontschieder, M. Fiterau, A. Criminisi, and S. R. Bul`, "Deep Neural Decision Forests," in Proceedings of the IEEE International Conference on Computer Vision, 2015, pp. 1467-1475.

12.P. Peng, K. Lekadir, A. Gooya, L. Shao, S. E. Petersen, and A. F.Frangi, "A review of heart chamber segmentation for structural and functional analysis using cardiac magnetic resonance imaging," MAGMA, vol. 29, pp. 155-95, Apr 2016.