Brain Region Segmentation by Using the Convolution Neural Networks

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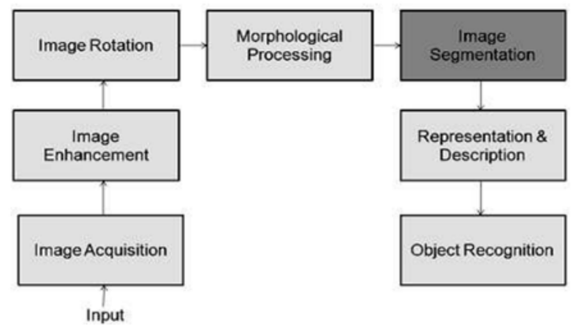
***Abstract*- Brain region segmentation or skull stripping is an essential step in neuroimaging application such as surgical, surface reconstruction, image registration etc. The accuracy of all existing methods depends on the registration and image geometry. When this fails, the probability of success is very less. In order to avoid this, Convolutional Neural Network (CNN) is used. For brain extraction which is free from geometry and registration. CNN learned the connectedness and shape of the brain. OASIS database is used which is publicly available benchmark dataset. In this method, training phase uses 30images and 10 images are used for testing phase. The performance of CNN results is closer to the ground truth results given by experts.**

Index terms- Brain region segmentation, skull stripping, MRI, convolutional neural network.

I. INTRODUCTION

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 Neuro imaging 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. . 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. Image segmentation is one of the-most important steps in image partitioning and their analyses. It can be used for various applications in computer vision and digital image processing. Many of the applications require highly accurate and computationally faster image processing algorithms.



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. Thresholding is one of the simplest approaches for image segmentation based on intensity levels. Threshold based technique works on the assumption that the pixels falling in certain range of intensity values represents one class and remaining pixels in the image represents the other class. The pixels satisfying threshold test are considered as object pixels with binary value ‘1’ and other pixels are treated as background pixels with binary value ‘0’. threshold is very crucial in image segmentation process. Threshold value can be determined either by an interactive way or can be the outcome of automatic threshold selection method. A single global threshold partitions image into objects.

II. RELATED WORK

Many methodologies have been developed for brain region segmentation. Noise and Intensity In homogeneity are two main obstacles. Therefore, noise removal is to be undertaken before further analysis of images. Non Local Mean filter algorithm is developed to remove the Rician noise A new similarity measure is used to remove the Rician noise based on that pixel value. 3D convolutional neural network is used for brain region segmentation process. Fully convolutional networks are trained in two ways one for patch wise prediction and another one for supervised pre training. The brain tumor segmentation is mainly focused on network architecture and it learn complex feature from the data itself. It is based on both discriminative and generative model. Discriminative method learns the correlation between the input image and ground truth image and it mainly depends on feature extraction. Generative model are used to extract the tumor cells. 3D CNN architecture is used for multimodality glioma segmentation task. Input image is processed at multiple scales simultaneously by using dual pathway architecture. By classifying each voxel in an image it takes the neighborhood, i.e. local and contextual information into account and it is estimated by voxel wise method.

III. LITERATURE SURVEY

Medical image acquisition devices provide a vast amount of anatomical and functional information, which facilitate and improve diagnosis and patient treatment, especially when supported by modern quantitative image analysis methods. However, modality specific image artifacts, such as the phenomena of intensity in homogeneity in magnetic resonance images (MRI), are still prominent and can adversely affect quantitative image analysis. In this paper, numerous methods that have been developed to reduce or eliminate intensity in homogeneities in MRI are reviewed. First, the methods are classified according to the in homogeneity correction strategy. Next, different qualitative and quantitative evaluation approaches are reviewed. Third, 60 relevant publications are categorized according to several features and analyzed so as to reveal major trends, popularity, evaluation strategies and applications. Finally, key evaluation issues and future development of the in homogeneity correction field, supported by the results of the analysis, are discussed. Methods for intensity in homogeneity correction in MR images have been reviewed. Additional insight into the field of intensity in homogeneity correction was provided by a detailed analysis of numerous publications that appeared in the last two decades. A number of important issues have been emphasized, indicating that intensity in homogeneity correction is still not a completely solved problem. Because of this and also because of the evolving MRI technology and associated applications, the problem of intensity in homogeneity correction will certainly continue to receive a lot of scientific attention in the future. Besides, validation issues should receive much more attention than in the past. combining Non-Local Means (NLM) filter with appropriate fuzzy cluster criterion, denoising in synthetic brain Magnetic Resonance Imaging (MRI) are evaluated. Non-local means (NLM) is a patch based image denoising method which exploits natural structural redundancy in a noisy image to restore higher quality image. Here, a combined method of non-local means and fuzzy cluster is presented for brain MRI denoising. Quantitative and qualitative results are compared with the NLM denoising method and wavelet-method, and results show that our proposed method can not only suppresses the noise more effectively but also well preserves the continuous edge and detailed structure for brain MRI. A problem to be resolved is the automatic selection of NLM parameters according to the medical image. In our experiment, default values of NLM method are used and good image quality is gained. In the future, automatic selection on parameters will be investigated to satisfy personalized preferences, which is expected to achieve better image quality.

IV. PROPOSED METHODOLOGY

In this 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. Fig. 1 shows the flow diagram of proposed methodology. 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.

4.1 PREPROCESSING:

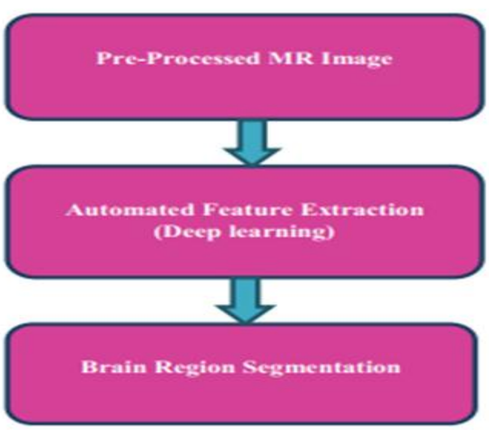
The MR images are first given to pre-processing step to enhance the quality of image for segmentation. In this work, Non Local Mean Filter is used for image denoising which calculates weighted average of pixels and finding similarity with the target pixel. It consists of four steps. Step 1: The weighted average non-local pixel is used to consider the data redundancy among the "patches" of the noisy image, and the noise free pixel is restored. The restored intensity, NL[u(xi)]of the noisy pixel u(xj) in the search window Vi is given by, equation that helps the radius of the search window in the second step weight estimate between two neighborhood patches.

$$NL(u(\mathrm{x_i})) = \sum_{x_{j} \epsilon V_j}^{\infty} \mathrm{W}(\mathrm{x_i} + \mathrm{x_j})\mathrm{U}(\mathrm{X_j})$$

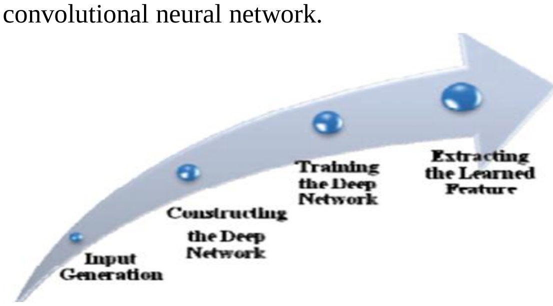
By using the above formula we can find the noisy of the window by intensity values. the weight estimate similarity between the intensity of two neighborhood patches concentrate on the voxels estimated by the variable of exponential decay control, h is given by the K where K is smoothing papameter and noise.

4.2 CONVOLUTIONAL NEURAL NETWORKS:

The denoised image is given as an input of CNN. Brain region segmentation by deep learning involves feature extraction as shown in Fig. 2. The learned features are learned using deep learning networks such as CNN for supervised learning. In this work, CNN generates accurate brain region segmentation. ConvNet architectures make the explicit assumption that the inputs are images, which allows us to encode certain properties into the architecture. These then make the forward function more efficient to implement and vastly reduce the amount of parameters in the network.

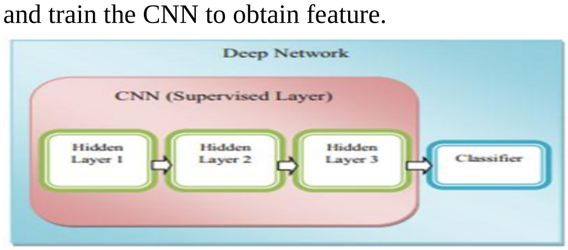


CNNs use a variation of multilayer perceptions designed to require minimal preprocessing. They are also known as shift invariant or space invariant artificial neural networks (SIANN), based on their-shared-weights architecture and translation invariance characteristics. CNN learns features directly from an image and no handcrafted features are needed. The method consists of three steps such as input data generation, construction of model and learning the parameter. So, a compact representation from the image as image patches are given as input data to the multilayer convolutional neural network. The supervised deep network consists of three layers. CNN learns features directly from an image and no handcrafted features are needed. The method consists of three steps such as input data generation, construction of model and learning the parameter. So, a compact representation from the image as image patches are given as input data to the multilayer convolutional neural network.



A CNN is different from the ordinary back propagation neural network (BPN) because a BPN works on extracted handcrafted image features whereas, a CNN works directly an image to extract useful, and necessary features for segmentation. A CNN consists of a number of convolutional layers, pooling layers and fully connected layers followed by one classification layer. When the size of the image is given as input to the CNN feature maps are produced by convolving the image with the filters.

The implementation steps are input generation, constructing the deep network, training the deep network and extracting the learned features. CNN can be done in three ways. The first method is to build and train the CNN to obtain feature.



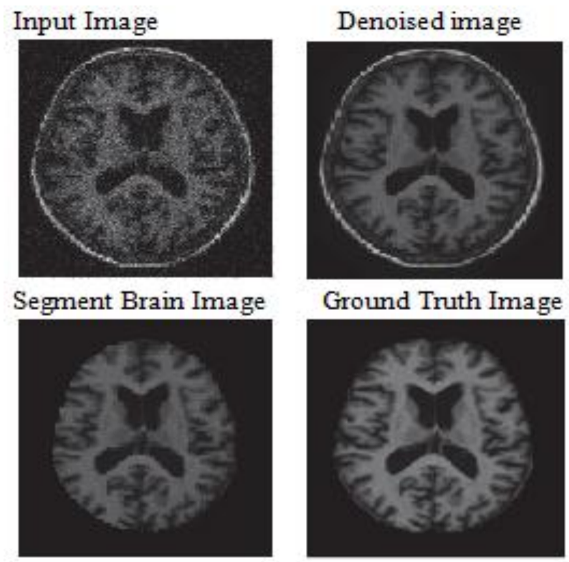
The second method is to use "off-the-shelf CNN features" without retraining the CNN. The third method is to use CNN in fine-tuning the results obtained using deep learning model. The first technique is used in building the CNN in this work. The CNN is constructed with 3 layers as shown in Fig. 4. In each hidden layer one convolutional layer and one pooling layers are present followed by one fully connected layer. It combines all the features learned by the previous layer across the image to identify the larger pattern.

V.EXPERIMENTAL RESULTS

The MRI images from publicly available OASIS Database were used in the supervised deep learning brain region segmentation. The OASIS is an organization of Washington research groups interested in the understanding of MRI and it has generated a database of digital MRI images. In this work 30 training images and 10 testing images in ages from the database are used. Noisy MR images are given to the denoising process, which uses Non Local Mean Filters. Based on the similarity measure between the weighted mean of all filters on image pixel and target pixel, it removes the Rician noise from MRI images. After getting denoised image, it is given as an input for brain region segmentation process. Brain region segmentation is performed using Convolutional Neural Network (CNN). CNN is trained iteratively with representative input patterns along with target label. Trained CNN is tested with unseen images. Fig. 5 shows the qualitative result of denoised and brain region segmentation images.

Input Images	Noise images Image PSNR (dB)	Sensitivity (%)	Specificity (%)	Accuracy (%)
Image1	51.468	87.1	96.7	98.1
Image2	51.954	89.6	99.1	94.2
Image3	51.236	98.1	97.1	97.6
Image4	51.324	96.3	94.4	95.4
Image5	50.982	92.6	98.1	95.3

From that it is observed that optimum PSNR values are obtained for the denoising using Non Local Mean filter algorithm and the high Accuracy, Sensitivity, and Specificity are obtained for brain region segmentation using Convolutional Neural Network. the below are output for image1.out of five image.



VI.CONCLUSION

Convolutional Neural Network (CNN) is used for brain region segmentation. The publicly available MRI database called OASIS are used in this work The MRI images are first pre-processed to remove Rician noise by using Non Local Mean (NLM) filter and non-brain tissues (skull portion) are removed by using CNN. One of the advantage of CNN is no handcrafted feature are needed; it learns features directly from the images. The performance of the CNN gives high accuracy in range of 92% to98%. In future work, the normal tissues such as white matter grey matter, and cerebrospinal fluid can be segmented by using computational intelligence techniques. Based upon the volume changes from these tissues, the disorders in brain can be identified.

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