Brain Region Segmentation using Convolutional Neural Network

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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 30 images and 10 images are used for testing phase. The performance of CNN results is closer to the ground truth results given by experts.**

Keywords— 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 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. RELATED WORK

Many methodologies have been developed for brain region segmentation. Noise and Intensity Inhomogeneity are two main obstacles. Therefore, noise removal is to be undertaken before further analysis of images [1]. Non Local Mean filter algorithm is developed to remove the Rician noise [2]. A new similarity measure is used to remove the Rician noise based on that pixel value [3]. 3D convolutional neural network is used for brain region segmentation process [4]. Fully convolutional networks are trained in two ways one for patch wise prediction and another one for supervised pre-training [5].

Mohammad Havaei et al, [6] proposed CNN; it is different from image processing techniques. It uses both local features and global contextual features simultaneously. 2-phase training procedure is described in this paper; it is easy to predict the tumor labels. It improves the speed 30 times faster than state of the art method. Deep learning method provides accurate results. This method is more efficient and it evaluate large amount of data in MRI images [7]. 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 [8]. The cube of voxels and patches are extracted from MRI images, it is used as an input of the method. In this paper CNN is used to predict the tissue label from cube of voxel. For accurate brain lesion segmentation, 3D Convolutional Neural Network (CNN) is used, which is proposed by Konstantinos Kamnitsas [9]. 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. This is achieved by using sequential convolution of the input at the cascaded network and it reduces false positive rate. Deep CNN uses small convolutional kernels for glioma segmentation [10].

For more convolutional layer, it uses small kernel while having the same receptive field of bigger kernels. It has two 3×3 cascaded convolutional layers have the same effective receptive field for 5×5 layer but fewer weights. One of the advantages of using this method is to reduce the overfitting because smaller kernel has fewer weights than bigger kernel. Olaf Ronneberger [11] proposed convolutional network for biomedical image segmentation. This architecture consists of contracting path and symmetric expanding path. Contracting path is used for capture context and expanding path is used for precise localization. This network can be trained end-to-end from very few images and outperforms the prior best method (a sliding window convolutional network) for segmentation. This architecture has two 3×3 convolutional layer, in each layer ReLU function is applied. The number of feature channels is doubled at each down sampling step. Every step in the expanding path consist of an up sampling of the feature map, it reduces the number of feature channels. At final layer, softmax classifier is used for classifying different classes. The application of convolutional layer consists in convolving a signal or an image with kernels to obtain feature maps [12]. In training phase, the weights of the kernels change adaptively by backpropagation, in order to enhance the input. Usage of several-cascaded CNN architecture has been proposed, to increase the flexibility and speed of computation for medical image segmentation. In every layer, the output of the first layer is concatenated with the input of the second layer. It is used to learn the context information in CNN network. Pixel class prediction is learned from all CNNs. The predictions are regularized using a more global super pixel segmentation of the image.

In this work, MRI images are used. In pre-processing step, the Rician noise is reduced by using Non Local Mean (NLM) filter algorithm. Brain region segmentation is a major step in brain imaging applications before doing main processing and it refers to the removal of non-cerebral tissues like skull. From the denoised image, brain region is segmented by using Convolutional Neural Network. In this work, the method of the work is given in section III, experimental results are given in section IV and conclusion is dealt in section V.

III. 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.

A. 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, $NL[u(x_i)]$ of the noisy pixel u(x_j) in the search window V_i is given by,

$$NL(u(x_i)) = \sum_{x_j \in v_i} w(x_i, x_j)u(x_j) \quad (1)$$

Where, M is the radius of the search window V_i, $w(x_i, x_j)$ is the weight allocate to the noisy value u(x_j) to establish the intensity u(x_i) at voxel x_i.

Step 2: The weight estimate the similarity between the intensity of the two neighborhood patches N_i and N_j concentrate on voxels x_i and x_j is estimated by the weight such that $w(x, x_j) \in [0,1]$.

Step 3: The weight based on the squared Euclidean distance between intensity patches u(N_i) and u(N_j) is gives as,

$$w(x_i, x_j) = \frac{1}{2}\exp\left(-\frac{\left\|u(N_i) - u(N_j)\right\|_2^2}{h^2}\right) \quad (2)$$

Where, $\sum_{x_j \in v_i} w(x_i, x_j) = 1$ is ensured by the normalization constant, Z_i is the variable for exponential decay control, h is given by, h = kσ where k is the smoothing parameter and σ is the noise standard deviation. By using Non Local Mean filter algorithm the noise is greatly reduced. It is an effective method to reduce the noise and it takes less time. One of the advantages of using Non Local Mean (NLM) filter is it does not loss any information from the input image.

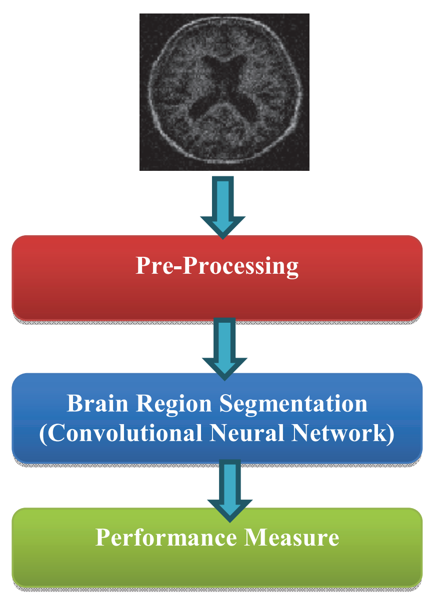

Fig 1. Flow Diagram of Proposed Methodology

B. Convolutional Neural Network

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.

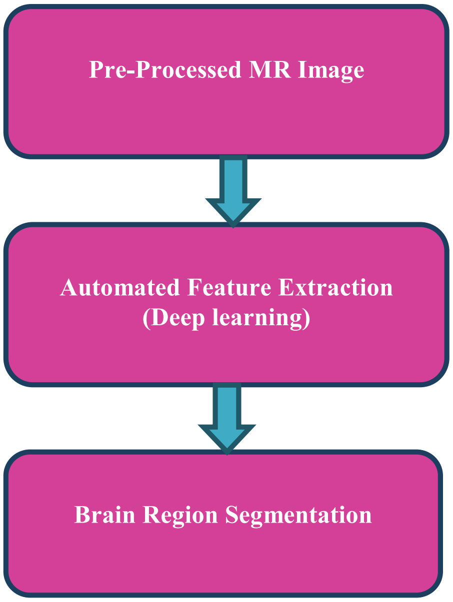

Fig 2.Brain Region Segmentation Steps

The architecture of "human –brain-inspired" deep nonlinear models compose complex features in the deeper layer of the network by analyzing the simple features learned in the previous layer. These features prove to be very effective descriptors in object recognition problems. During the training phase of these models, the features are encoded iteratively and then the learned weights are updated for improved optimization of the network. The features can be learned using CNN in supervised manner. The features learned in a layer wise method are fed into a trained classifier, which predicts the labels. The classifier being a supervised layer has been trained using a set of images along with the associated label. The trained network should be able to accurately predict the label for unseen images. The feature extraction using deep learning includes the following implementation steps: input generation, construction of the deep network, training the network and extracting the learned feature. The steps in feature extraction using CNN are shown in Fig. 3.

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. Input image is given to the input layer, it predict the label from input layer. In every hidden layer one convolutional layer and one pooling layer is Present. Convolutional layer compute a dot product of the weights, input, and add a bias term. In gray image, the bias term is always one. Pooling layer perform down sampling operation, it reduces the number of connections to the following layer.

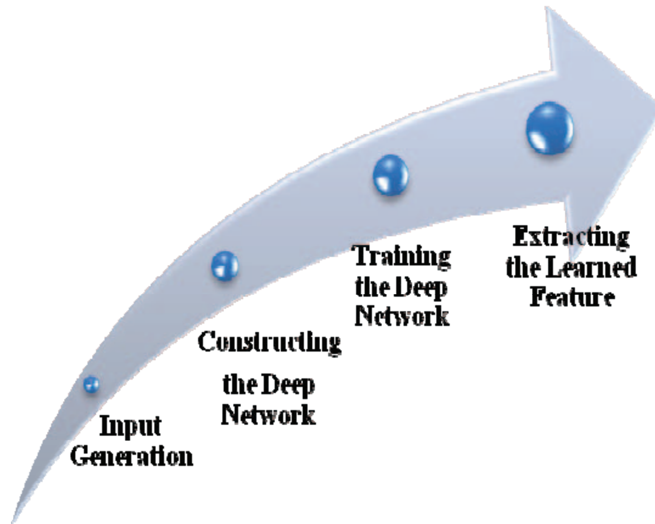

Fig 3.Steps in Feature Extraction using CNN

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. Each map is sub-sampled typically with mean or max pooling layers. Sub sampling rate usually varies from two to five. After the convolutional layers, there may be any number of fully connected layers.

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.

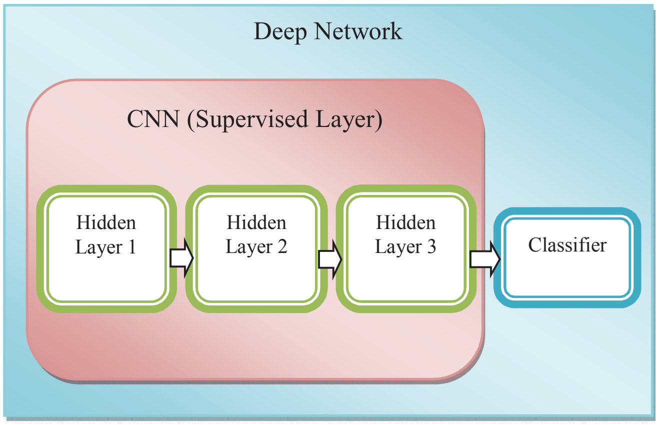

Fig 4.Construction of Convolutional Neural Network

IV. Result And Discussion

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.

Performance evaluation is important step in developing a segmentation algorithm for an image system. The performance can be evaluated either qualitatively or quantitatively. The qualitative results give visual representation and quantitative results provide numerical values. The PSNR value is calculated by,

$$PSNR = 10\log_{10}\left(\frac{f^2{}_{\max}}{MSE}\right) \tag{3}$$

$f^2{}_{\max}$ is the maximum possible pixel value of the image. MSE is the mean square error between the reconstructed image and original image. All segmentation results could have an error rate described by the terms true and false positive, true, and false negative. The performance of segmentation is measured in terms of Accuracy, Sensitivity and Specificity, which are given in (4), (5) and (6) respectively.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{4}$$

Sensitivity is given by,

$$Sensitivity = \frac{TP}{TP+FN} \tag{5}$$

Specificity is given by,

$$Specificity = \frac{TN}{TN+FP} \tag{6}$$

Where TP denotes True Positive, TN represents True Negative and FP, FN are False Positive & False Negative respectively. Table 1 shows quantitative results for denoised images and brain region segmented images.

TABLE 1

QUANTITATIVE RESULTS FOR DENOISED IMAGE AND BRAIN REGION SEGMENTATION IMAGES

Input images	Denoised image PSNR (dB)	Sensitivity (%)	Specificity (%)	Accuracy (%)
Image 1	51.4688	87.1	96.7	91.8
Image 2	51.9544	89.6	99.1	94.2
Image 3	51.2365	98.1	97.1	97.6
Image 4	51.3245	96.3	94.4	95.4
Image 5	50.9823	92.6	98.1	95.3

From the Table 1, 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.

Input Image Denoised Image Segmented Brain Image Ground Truth Image

Input Image 1

Input Image 2

Input Image 3

Input Image 4

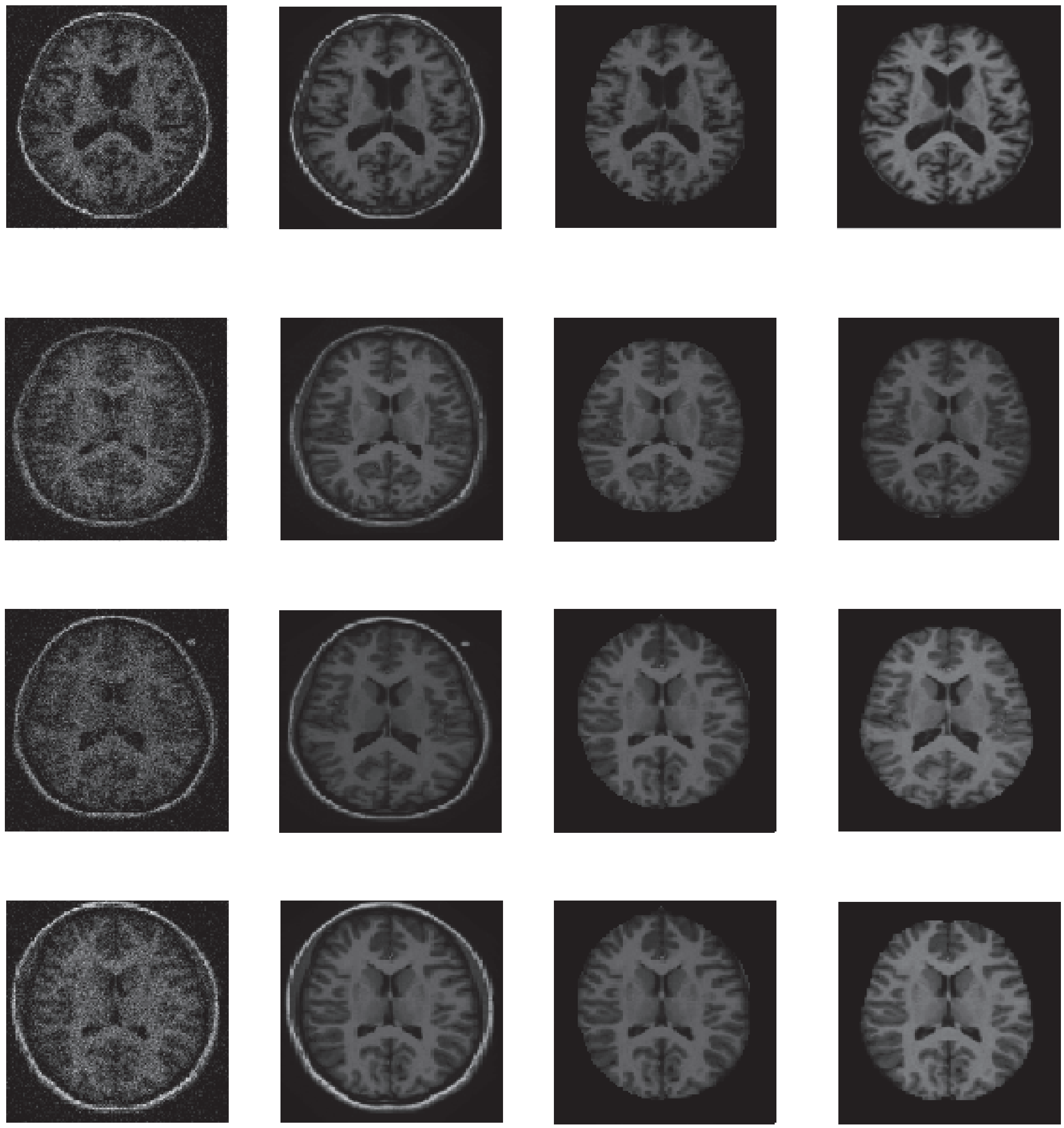

Fig 5.Qualitative Results for Denoised Image and Brain Region segmented Image

V. RESULT AND DISCUSSION

In the proposed work, 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 features are needed; it learns features directly from the images. The performance of the CNN gives high accuracy in the range of 92% to 98%. 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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