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BRAIN TUMOR SEGMENTATION USING CONVOLUTIONAL NEURAL NETWORKS IN MRI IMAGES

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Abstract:

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, I propose 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 over fitting, 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. My 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. I 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.

1. Introduction:

Image processing is processing of images using mathematical operations by using any form of signal processing for which the input is an image, a series of images, or a video, such as a photographer video frame; the output of image processing may be either an image or a set of characteristics or parameters related to the image. Most image-processing techniques involve treating the image as a dimensional signal and applying standard signal-processing techniques to it. Images are also processed as three-dimensional signals where the third-dimension being time or the z-axis. Image processing usually refers to digital image processing, but optical and analog image processing also are possible. This article is about general techniques that apply to all of them. The acquisition of images (producing the input image in the first place) is referred to as imaging. Image processing is a method to convert an image into digital form and perform some operations on it, in order to get an enhanced image or to extract some useful information from it. It is a type of signal dispensation in which input is image, like video frame or photograph and output may be image or characteristics associated with that image. Usually Image Processing system includes treating images as two dimensional signals while applying already set signal processing methods to them. It is among rapidly growing technologies today, with its applications in various aspects of a business. Image Processing forms core research area within engineering and computer science disciplines too.

- ✓ Analyzing and manipulating the image which includes data compression and image enhancement and spotting patterns that are not to human eyes like satellite photographs.
- ✓ Output is the last stage in which result can be altered image or report that is based on image analysis.

Image Processing Toolbox supports a diverse set of image types, including high dynamic range, giga pixel resolution, embedded ICC profile, and tomographic. Visualization functions and apps let you explore images and videos, examine a region of pixels, adjust color and contrast, create contours or histograms, and manipulate regions of interest (ROIs). The toolbox supports workflows for processing, displaying, and navigating large images.

2. Fundamental Steps in Image Processing:

Image Acquisition: To acquire a digital image.

Image Pre-Processing: To improve the image in ways that increases the chances for success of the other processes.

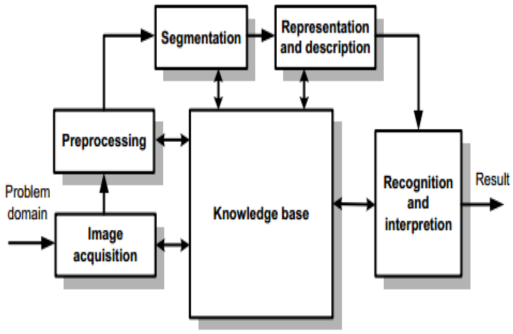
Image Segmentation: To partitions an input image into its constituent parts or objects.

Image Representation: To convert the input data to a form suitable for computer processing.

Image Description: To extract features that result in some quantitative information of interest or features that are basic for differentiating one class of objects from another.

Image Recognition: To assign a label to an object based on the information provided by its descriptors.

Image Interpretation: To assign meaning to an ensemble of recognized objects.



3. Convolutional Neural Networks:

In machine learning, a convolutional neural network (CNN, or ConvNet) is a type of feed-forward artificial neural network in which the connectivity pattern between its neurons is inspired by the organization of the animal visual cortex. Individual neurons of the animal cortex are arranged in such a way that they respond to overlapping regions tiling the visual field, which can mathematically by a convolution operation. Convolutional net works were inspired by biological processes and are variations of multilayer perceptron's designed to use minimal amounts of preprocessing. They have wide applications in image and video recognition, recommender systems and processing. The convolutional neural network is also known as shift invariant or space invariant artificial neural network (SIANN), which is named based on its shared weights architecture and translation invariance characteristics.

4. Image Recognition:

Convolutional neural networks (CNNs) consist of multiple layers of receptive fields. These are small neuron collections which process portions of the input image. The outputs of these collections are then tiled so that their input regions overlap, to obtain a better representation of the original image; this is repeated for every such layer. Tiling allows CNNs to tolerate translation of the input image. Convolutional networks may include local or global pooling layers which combine the outputs of neuron clusters. They also consist of various combinations of convolutional and fully connected layers, with point wise nonlinearity applied at the end of or after each layer. A convolution operation on small regions of input is introduced to reduce the number of free parameters and improve generalization. One major advantage of convolutional networks is the use of shared weight in convolutional layers, which means that the same filter (weights bank) is used for each pixel in the layer; this both reduces memory footprint and improves performance.

Time Delay and Neural Networks**:** Some time delay neural networks also use a very similar architecture to convolutional neural networks, especially those for image recognition or classification tasks, since the tiling of neuron outputs can be done in timed stages, in a manner useful for analysis of images. Compared to other image classification algorithms, convolutional neural networks use relatively little pre-processing. This means that the network is responsible for learning the filters that in traditional algorithms were hand-engineered. The lack of dependence on prior knowledge and human effort in designing features is a major advantage for CNNs

In the field of brain tumor segmentation, recent proposals also investigate the use of CNNs. used a shallow CNN with two convolutional layers separated by max-pooling with stride 3, followed by one fully-connected (FC) layer and a soft max layer evaluated the use of 3D filters, although the majority of authors opted for 2D filters . 3D filters can take advantage of the 3D nature of the images, but it increases the computational load. Some proposals evaluated two-pathway networks to allow one of the branches to receive bigger patches than the other, thus having a larger context view over the image. In addition to their two-pathway network, built a cascade of two networks and performed a two-stage training, by training with balanced classes and then refining it with proportions near the originals binary CNN to identify the complete tumor. Then, a cellular automata smooths the segmentation, before a multiclass CNN discriminates the sub-regions of tumor extracted patches in each plane of each voxel and trained a CNN in each MRI sequence; the outputs of the last FC layer with soft max of each CNN are concatenated and used to train a RF classifier the ´ brain tumor regions segmentation tasks into binary sub-tasks and proposed structured predictions using a CNN as learning method. Patches of labels are clustered into a dictionary of label patches, and the CNN must predict the membership of the input to each of the clusters. In this paper, inspired by the groundbreaking work of on deep CNNs, we investigate the potential of using deep architectures with small convolutional kernels for segmentation of gliomas in MRI images proposed the use of small 3 × 3 kernels to obtain deeper CNNs. With smaller kernels we can stack more convolutional layers, while having the same receptive field of bigger kernels. For instance, two 3×3 cascaded convolutional layers have the same effective receptive field of one 5×5 layer, but fewer weights. At the same time, it has the advantages of applying more non-linarites and being less prone to over fitting because small kernels have fewer weights than bigger kernels. We also investigate the use of the intensity normalization method proposed as a pre- ´ processing step that aims to address data heterogeneity caused by multi-site multi-scanner acquisitions of MRI images. The large spatial and structural variability in brain tumors are also an important concern that we study using two kinds of data augmentation.

Pre-Processing: MRI images are altered by the bias field distortion. This makes the intensity of the same tissues to vary across the image. To correct it, we applied the N4ITK method. However, this is not enough to ensure that the intensity distribution of a tissue type is in a similar intensity scale across different subjects for the same MRI sequence, which is an explicit or implicit assumption in most segmentation methods. In fact, it can vary even if the image of the same patient is acquired in the same scanner in different time points, or in the presence of a pathology. So, to make the contrast and intensity ranges more similar across patients and acquisitions, we apply the intensity normalization method. In this way, the histogram of each sequence is more similar across subjects. After normalizing the MRI images, we compute the mean intensity value and standard deviation across all training patches extracted for each sequence. Then, we normalize the patches on each sequence to have zero mean and unit variance1.

5. Conclusion:

In summary, I propose a novel CNN-based method for segmentation of brain tumors in MRI images. We start by a pre-processing stage consisting of bias field correction, intensity and patch normalization. After that, during training, the number of training patches is artificially augmented by rotating the training patches, and using samples of HGG to augment the number of rare LGG classes. The CNN is built over convolutional layers with small 3 × 3 kernels to allow deeper architectures. In designing our method, we address the heterogeneity caused by multi-site multi-scanner acquisitions of MRI images using intensity normalization as proposed by Nyul et al. This is important in achieving a good segmentation. Brain tumors are highly variable in their spatial localization and structural composition, so we have investigated the use of data augmentation to cope with such variability. It studied augmenting our training data set by rotating the patches as well as by sampling from classes of HGG that were underrepresented in LGG. We found that data augmentation was also quite effective, although not thoroughly explored in Deep Learning methods for brain tumor segmentation.

Output:

Home Page:

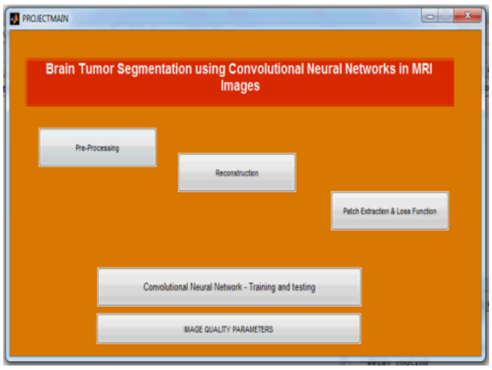


Figure 1: Home Page

Pre-Processing, Reconstruction, Patch Extraction are done by using Matlab Software. Convolutional neural network is the heart of this project. The qualities of the images are considered for features.

Image Recognition:

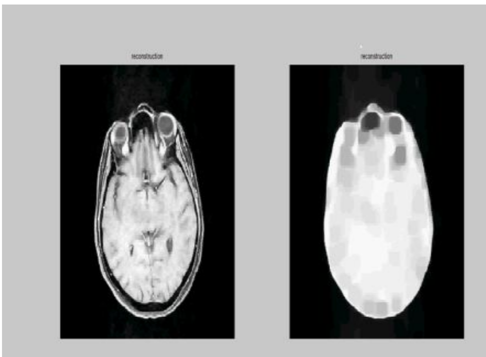


Figure 2: Image Recognition

The images were taken from the data base and is reconstructed. The reconstructed image is shown in the above figure .The reconstructed image has only white and grey matter.

Patch Extraction:

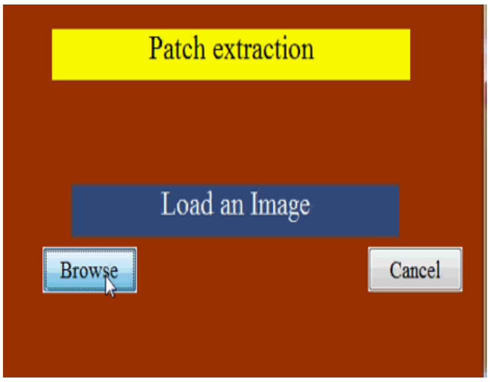


Figure 3: Patch Extraction

In this patch extraction we are going to extract the image and is compared with the normal brain image. It is stored already and its features are compared. If there is any then the abnormalities will be taken into account and it will be calculated.

Comparison:

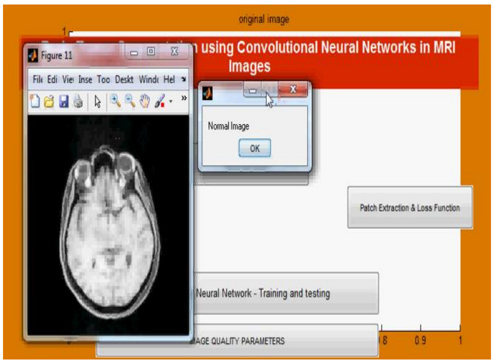


Figure 4: Comparison of Normal Image with its Brain Tumour Image

Image Showing Tumor:

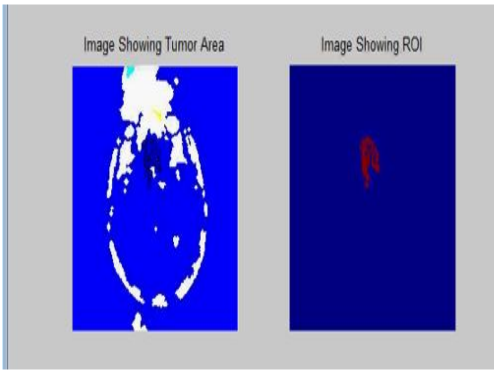


Figure 5: Image Showing Tumor

This is the image showing the tumour in the brain. The tumour area is clearly visible in this image

Output for Phase I:

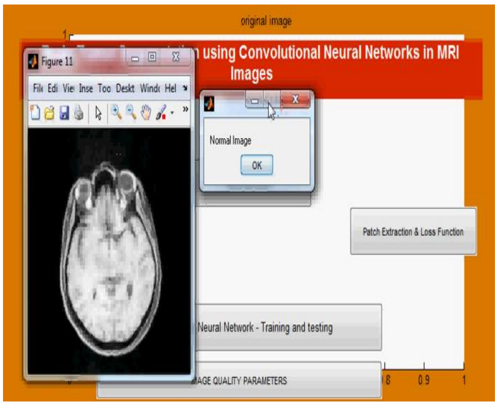


Figure 6: Comparison of Normal Image with Its Brain Tumour Image

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