An Approach to Brain Tumor Segmentation using Convolutional Neural Networks

Sunil Tulabandula[1], Anesh Indla[2], Mayur Dhanwat[3], Pravin Badadapure[4]
[1, 2, 3, 4] Department of Electronics and Telecommunication
[1, 2, 3, 4] JSPM's Imperial College of Engineering and Research

Abstract- *Nowadays brain tumors have become very serious issue. Considering different types of brain tumors, the most common and aggressive tumors are Gliomas. These gliomas lead to a very short life span of patients if the tumor is of High grade and if the tumor is of Low grade then the life span is of several years. Thus, proper planning for the respective treatment is very important to improve the life span of oncological patients.*

Magnetic Resonance Imaging (MRI) is a popular and widely used medical imaging technique to evaluate the brain tumors. While using MRI scans to assess the brain tumors a large amount of data is generated that limits it for manual segmentation. Also manual segmentation of these MRI scans consumes too much time of the clinical professionals. Even after considering all these limitations of manual segmentation, the output that we obtain is not very accurate and reliable.

So, there is a need for automatic and reliable segmentation method. But the size, shape and location of brain tumor varies for different patients and these features makes it as a difficult task to design the automatic segmentation method. In this paper, we propose a fast and an automatic segmentation method using Convolutional Neural Networks (CNN). Here we use small 3x3 kernels that allows designing of a deeper neural network architecture. The use of these small kernels removes the problem of overfitting and provides less number of weights that are very easy to handle in the designed network.

Keywords- Convolutional Neural Networks, Magnetic Resonance Image (MRI), Brain Tumor Segmentation, Gliomas, Neural Network Architecture.

I. INTRODUCTION

A tumor is formed when a cluster of unhealthy cells form in the brain. There are many different types of brain tumors. For example; cancer tumors and benign tumors. These cancer tumors can further be classified as primary tumors and secondary tumors. Primary tumors are the tumors that are formed within the brain and Secondary tumors are the tumors that are formed at some place and start spreading to different corner. On the other hand benign tumors are the tumors that are not very risky and thus they are just cluster of cells.

Among all the brain tumors, Gliomas are the tumors in brain that are very aggressive and cause maximum deaths in human beings. These Gliomas can be classified into Low Grade and High Grade. The Gliomas with Low Grade is not very aggressive but the Gliomas with High Grade is very aggressive with highest mortality. Even after diagnosis for Gliomas with High Grade, the patients on an average do not live more than 1 year. Patients do take treatments that are currently in use, they are surgery, chemotherapy, radiotherapy or a combination of them.

MRI is a technique in medical field that is used to take scanning images of different parts of body. MRI is used to evaluate the gliomas practically and get the required information to classify the brain tumor for further treatments.

The perfect segmentation of gliomas and tumors in brain is very important for daily basis evaluations and further treatment planning. But, segmenting the MRI with manual method is a very hectic and time consuming. Also manual segmentation causes classification errors while classifying the inner and in between cells making it difficult for characterization. Thus, doctors find it difficult to classify and do not prefer rough measures. For all these reasons, automatic and accurate segmenting methods are required for segmentation of tumors.

The symptoms are varying based on the location, shape, size of the tumor present in brain. Thus it becomes a challenging and difficult task to design a segmentation technique. Also, the arrangement and position of normal tissues gets affected as abnormal tumor is present in the vicinity. MRI scans also give some problems such as intensity variations while acquiring the MRI scans from the scanners [1].

These fluctuating intensities distortion can be corrected using pixel approximation technique as described by Prof. Nicholas J. Tustison using N4ITK method [1]. The intensities of the neighboring pixels should be normalized.

Thus for normalizing the intensities we use intensity normalization method as described by Prof. Laszlo G. Nyul [2].

Now automatic segmentation is required for accurate and reducing the burden of the doctors, thus by using CNN technique segmentation of the tumors is carried out as described by many different authors in different papers [3] [7].

II. METHODOLOGY

In this paper, we have implemented the technique for segmentation of tumors in brain. The whole method can be described in different sections: Pre-processing, Super Resolution Algorithm, Patch extraction & Processing, Feature Extraction, and Segmenting using CNN, Output Image.

A. Pre-processing:

MRI is a popular mostly used imaging technique to evaluate the brain tumors. Any pre-processing step always tries to detect the disturbance created by MRI scanners during the acquisition of MRI images. MRI images are mainly affected by bias field distortion during their acquisition. This distortion results in varying the intensities of same tissue pixels in many different parts of the image. To correct the distortion occurred we apply the Nonparametric Non-uniform Intensity Normalization (N4ITK) algorithm which is available to the public through Insight Toolkit of the National Institutes of Health. This algorithm uses approximation method that is similar to neighbourhood processing which includes averaging the neighbouring pixels and replacing it in the central pixel.

B. Super Resolution Algorithm:

Correcting the bias field distortion is not enough to confirm that intensities of the same tissues at different regions in image have same intensity levels. It may so happen that the MRI scans have varying intensities for the same patient with same scanner for different acquisitions. So to make the intensities and contrast of pixels more similar for the patients and acquisitions, we now apply intensity normalizing technique. In this intensity normalizing technique, for the training phase a set of intensity landmarks are learned for each sequence. Now the original intensities are linearly transformed between the two landmarks into the corresponding learned landmarks so as to get the required intensity normalization. Due to this, the intensities of each corresponding sequence is more similar in same tissues.

Now we calculate mean of the intensity values and standard deviation in each sequence for all training patches that are extracted. Later we also normalize the patches on each sequence to have zero mean and unit variance.

C. Patch Extraction & Processing:

In image processing the idea of scanning an image is done using small shape or small templates also known as kernels or structuring element. These kernels need to have an origin because the operation of these also produces some result. This result is taken as the output of the process corresponding to the current location of the origin in kernel. Thus the kernel is commonly defined to have odd size, and the central pixel is used as the origin of kernel. For example, 3x3, 5x5, 7x7 etc.

For the process of scanning the input MRI images we define different 3x3 kernels based on trial and error basis. To extract the patches in MRI images it is necessary to define a plane perpendicular with the kernels. The patches that are extracted at this stage are further processed to obtain the features of the MRI images.

D. Feature Extraction:

Feature extraction is a process in which we have to extract the features from the improved image. Using DCT we can obtain the absolute coefficients of the enhanced images. Absolute coefficients give the maximum information of an image. So we have selected absolute coefficients for feature extraction. We extracted different features like Contrast, Correlation, Energy, Homogeneity, Mean, Standard Deviation, Entropy, RMS, Variance, Smoothness, Kurtosis, and Skewness. These features are further used foe brain tumor detection. These features are useful in determining the class and type of object present in the image.

E. Convolutional Neural Networks:

A CNN is a system of artificial neurons that are interconnected and exchange data between different neurons. There are connections from a neuron to the other neuron and the connections have weights on them that are set at the time of training process. Thus a properly trained network will give output correctly when it is applied with a pattern to detect an object in a picture. These networks are consisting of different layers of feature-detecting neurons. Every layer contains many neurons that give different output for different combination of input values.

CNN are used to obtain feature maps by convolving an image with 3x3 kernels. The contents or values in feature maps are connected to the values in previous layers via weights of the mask. The weights of the mask are decided are decided during the training phase of the network. The weights of the neurons are updated by using a process called Back-Propagation. As CNN uses same mask for convolution, the same features are detected at any location in the image. We use a Non-linear activation function to activate the neurons in the feature maps.

By stacking many convolutional layers we get more accurate features of the network.

Some important concepts used in CNN are:

1) Convolution Layer:

It is the first layer that is formed after the process on the applied image. Different features get extracted from the applied image in convolution operation. Low-level features like edges, lines, and corners are obtained in the first convolutional layer. At a later stage High-level features are obtained at higher-level layers.

2) Pooling Layer:

The function of pooling/subsampling layer is to reduce the size of feature maps. Pooling reduces the number of parameters and computations in the network and it also makes the features more robust against distortion and noise. The reduction of parameters limits the overfitting problem. This Layer performs operation independently on every group of the input feature maps and reduces the layer size using a MAX function.

3) Non-Linear Layer:

CNN particularly depend on a non-linear trigger function to activate the particular neurons and to identify features on each hidden layers. CNN uses different functions for triggering of neurons such as continuous trigger (non-linear) and rectified linear units (ReLUs) function.

i) Rectified Linear Unit (ReLU):

The size of input and size of output of this Non-linear layer are same, as a ReLU is implemented. We used ReLU in our network to activate the neurons. The ReLU function is;

$$y = \max(x,0)$$

ii) Continuous trigger (non-linear) function:

When Non-linear functions are applied to the non-linear layer then it operates value by value for each feature. Different Non-linear trigger functions can be absolute of hyperbolic tangent, hyperbolic tangent, or sigmoid.

4) Fully Connected Layer:

A FC Layer is attached at the end of the network and used to find out the high level features. The FC layer takes the input from the previous layers that are attached in the network that are convolution layer or Non-linear layer or pooling layer. This layer gives an output of N Dimensional vector; where N represents number of classes that a program has to select the right output.

A FC Layer functions such that it sees at the output of the previous layers and determines that which features correlate the most to a specific class, and we know that these features represent activation maps of high level features. Thus a FC layer sees at the high-level features that mostly relate to a specific class and has specific weights, so that when we compute the products between the weights and the previous layer values, we will get the correct probabilities for the different classes.

5) Training of CNN:

Training is one of the most important concepts of Neural Networks. The way in which the program can be trained is called as Backpropagation. In this process the CNN accepts the applied image that has to be trained. The CNN processes the applied image and generates specific output that signifies a specific class with high-level features with the activation maps. Thus this output is compared with a desired output in a comparator. Now this comparator will generate an error based on the difference of both the outputs. Then this error is given back to the CNN for adjustment of the weights. This process continues until we get a null error. The entire process is known as Backpropagation.

This backpropagation process can be divided into 4 sections;

i) The forward pass:

In the forward pass section, we take an image that is to be trained, let us consider an example with the image size of 32x32x3 and it is passed through the entire network. This is the first example of training an image, so the weights will be randomly initialized and we will get the output that will have probabilities like [.1 .1 .1 .1 .1 .1 .1 .1 .1 .1], that is an output that doesn’t give preference to any particular number. The CNN with its present weights is not able to find those low-level features nor is it able to make a perfect conclusion.

ii) The Loss function:

After the forward pass the output goes to the loss function, and we know that training data has both an image and a label as we are using the training data. Let us consider an example the first training input image is 3 and the label of the image would be [0 0 0 1 0 0 0 0 0 0]. A loss function can defined in many ways but the most commonly used loss function is Mean Squared Error (MSE).

$E_{Total} = \sum ½ (Target – Output)^2$

Let us consider a variable L that is having certain value. Then we can say that initially the loss is extremely high for the first few training images. Now we want to get to a point where the output label is the same as the target label. This determines that our network prediction is correct. To get this, we have to minimize the amount of loss.

iii) **Backward pass:**

Backward pass can be defined in the form of a mathematical equation that is dL/dW, where W represent the weights. In backward pass we determine the weights that contribute most of the loss and find ways to adjust the weights to decrease the loss. After computing this derivative then we proceed to the further step.

iii) Weight update:

In this step we consider the weights of all the masks and update them so that they change in the direction of the gradient.

$W = W_i – \eta (dL/dW)$

Where w is the weight, Wi is the initial weight, η is the learning rate. Here the learning rate is decided by the designer. Thus for high learning rates bigger steps are to be taken in weight updates. Thus it takes less time to reach for optimal set of weights. Thus a very high learning rate will result in jumps that are too large and not accurate enough to reach the optimal point.

6) Testing of CNN:

At last we have to see that whether our CNN works properly or not, so we have a different set of images and labels and pass the images through the network. Then we compare the outputs with the required output and verify whether our CNN works.

7) Output Image:

At this stage we obtain the segmented image using CNN and we can observe the tumor segmented out from the input image.

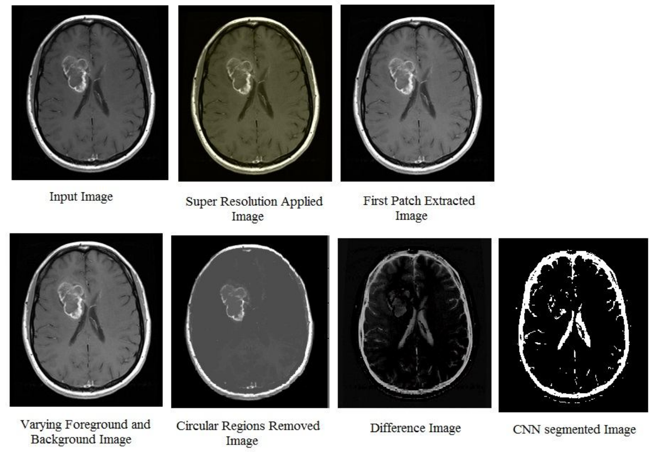

Figure 1. explains the whole segmentation implementation images

III. CONCLUSION

We developed a system for segmenting the brain tumors using CNN. Firstly we start off with a pre-processing step in which we face bias field distortions. To correct these bias field distortions we apply N4ITK algorithm that is based on approximation of pixels method. After that we normalize the intensity of the pixels. Later on we train the network with different MRI scans to achieve a better output. The CNN architecture is built over many hidden layers that use small 3x3 kernels to get more deep architectures.

After designing our model, we found that our system was quite fast in generating the CNN segmented output and also provide satisfactory accuracy but it is not 100% accurate.

REFERENCES

[1] N. J. Tustison et al., “N4itk: improved n3 bias correction,” IEEE Transactions on Medical Imaging, vol. 29, no. 6, pp. 1310–1320, 2010.

[2] L. G. Ny´ul, J. K. Udupa, and X. Zhang, “New variants of a method of mri scale standardization,” IEEE Transactions on Medical Imaging, vol. 19, no. 2, pp. 143–150, 2000.

[3] R. Rewari, “Automatic Tumor Segmentation from MRI scans” report from Stanford University, raunaq@stanford.edu

[4] B. H. Menze et al., “A generative model for brain tumor segmentation in multi-modal images,” in Medical Image Computing and Computer- Assisted Intervention–MICCAI 2010. Springer, 2010, pp. 151–159.

[5] S. Bauer, L.-P. Nolte, and M. Reyes, “Fully automatic segmentation of brain tumor images using support vector machine classification in combination with hierarchical conditional random field regularization,” in Medical Image Computing and Computer-Assisted Intervention–MICCAI 2011. Springer, 2011, pp. 354–361.

[6] D. Zikic et al., “Decision forests for tissue-specific segmentation of high-grade gliomas in multi-channel mr,” in Medical Image Computing and Computer-Assisted Intervention–MICCAI 2012. Springer, 2012, pp. 369–376.

[7] A. Davy et al., “Brain tumor segmentation with deep neural networks,” MICCAI Multimodal Brain Tumor Segmentation Challenge (BRATS), pp. 31–35, 2014.

[8] A. Pinto et al., “Brain tumor segmentation based on extremely randomized forest with high-level features,” in Engineering in Medicine and Biology Society (EMBC), 2015 37th Annual International Conference of the IEEE. IEEE, 2015, pp. 3037–3040.

[9] www.wikipedia.com

[10] www.ieeexplore.ieee.org

[11] www.github.com