# Review on Brain Tumor Segmentation Methods using Convolution Neural Network for MRI Images

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***Abstract* — An efficient and timely detection of brain tumors will aid the better treatment selections and improves the survival rate of the patients. The segmentation processes of Magnetic resonance images (MRI) play a crucial role in detecting brain tumors. Since the large amounts of MRI images are generated during the cancer diagnosis, manual image segmentation will be a tedious job due to time constraints. An automatic image segmentation processes can alleviate the former limitation. There are various algorithms used to segment the images automatically, in which the deep learning technique is more efficiently used for large amount of images to find the size and location of a cancer. Enormous review papers have been published to give insight on MRI-based image segmentation. Our review is focused on Convolutional Neural Network (CNN) based deep learning algorithm, as it gives better accuracy in image recognition problems.**

***Keywords—Brain tumor, brain tumor segmentation, convolutional neural networks, deep learning, glioma, magnetic resonance imaging***

## I. Introduction

The uncontrolled division of the cells in the body is defined as cancer and the brain tumor is the occurrence of abnormal cell growth in brain tissues. Brain tumor is one of the most dangerous cancers. Primary brain tumors and metastatic brain tumors are the two types of brain tumors based on their initial origin. Primary brain tumors has its origin is in brain tissues cells whereas metastatic brain tumors originates in some other part of the body and it spreads into the brain. Glioma is one of the most common and life threatening type of metastatic brain tumors that originate from glial cells. Gliomas can be categorized as Low Grade Gliomas (LGG) and High Grade Gliomas (HGG). LGG are less aggressive whereas HGG are more aggressive [1],[2].

Radiotherapy, surgery, chemotherapy or a combination of these techniques [3] are used for the treatment of brain tumors. The most common treatment is surgery whereas radiotherapy and chemotherapy are used to reduce the growth of tumor cells. Diagnosis plays an important role in improving the treatment. Magnetic Resonance Spectroscopy (MRS), Computer Tomography(CT), Positron Emission Tomography(PET), Magnetic Resonance Imaging (MRI) are the techniques used to provide information such as location, size, shape of the tumor which are used in diagnosis.

MRI is one of the standard imaging technologies which provides detailed images of the brain providing complementary information [4] which are used to diagnose brain tumors. Different regions, size, shape and volume of the tumor can be identified from the sequence of images such Flair, T1, T1 contrast, T2, etc., which are generated using MRI technique. Brain tumor segmentation from MRI has great impact on diagnostics, and treatment planning. However, manual segmentation is time-consuming procedure and subjected to errors. Therefore, the automatic and semi-automatic tumor segmentation algorithms are required to improve the accuracy in segmentation which in turn improves the success rate of brain tumor treatment. However, it is a challenging task, since the structure, location, and shape of these abnormalities are highly variable.

Feature selection is the important limitation among various difficulties in brain tumor segmentation. But, in deep learning models the input can be spontaneously used to learn the features of the objects. In recent years, Convolutional Neural Networks (CNNs) which is one of the most popular deep learning models have been used for MRI-based brain tumor segmentation since it is a powerful tool for feature detection and extraction. The following section provides an insight on segmentation techniques using CNN.

## II. Segmentation of Glioma tumors in brain using deep convolutional neural network

An ILinear nexus architecture was built by using batch normalization[6], maxout[7], dropout[5], inception module, non-linear activation [8]. Since, this architecture was built with dropout regulizer, it was efficiently applied to overcome the over-fitting issues arise during the insufficient data. In the pre-processing step, the image was normalized, the bias field was corrected, and the patches were extracted out. After which, the output label was generated for the central pixel of individual patch by passing the extracted patches through CNN. Consecutively, the post processing was done to fine tune the output label by using morphological operators. The performance parameter was enhanced by introducing a two-phase weighted training method on BRATS 2013 and BRATS 2015 datasets. Elaborate discussions on the steps involved in the application of CNN architecture are as follows.

### *1) Pre-processing*

The artefacts like motion and field inhomogeneity could impact on MR image and leads to false intensity level and output [8]. The artefact effects could be eliminated by bias field correction techniques using non-parametric, non-uniform intensity normalization (N3)/N4ITK algorithms [ref] to enhance the intensity values of the images. Further improvement in the mean intensity value and variance can be achieved through following equation (1).

$$x_n = \frac{\mathrm{x} - \mu}{\sigma} \tag{1}$$

Where xn is the normalized slice, x is the original slice, μ is the mean, and σ is the standard deviation of x.

*2) Convolutional Neural Network (CNN)*

There are several layers are present in CNN such as convolution, pooling, dense, dropout, etc. Among which the convolution layer in a CNN is the prime importance. The layers will be hierarchically stacked over others to form the feature maps. These feature maps serves as the input for the succeeding convolution layer except for the initial convolution layer which has the direct connectivity with the input space. The CNNs ability of learning the complicated features from the hierarchical feature maps made the CNNs a very useful tool in image recognition. The kernels of convolution layers will be convolved upon the sample inputs in order to compute the multiple feature maps. The output of the max-pooling layer is transferred to 1D vector in the fully connected layer. Non linear feature extractors are convolved with input planes to extract features.

The patches in the four input images from T1, T1C, T3, and T2-Flair has been processed by this proposed model for predicting the output label for all pixels of the relative patch, and the brain image could be segmented. The back-propagation method is used to learn the kernels and connections' weight [9]. The highest value of the feature is maintained in max-pool method. When concatenating two CNNs, the nexus architectures are produced. The first network's output is used to concatenate the second network input and forms the nexus. The first network takes 4 X 33 X 33 as inputs of four MR image modalities and produces the 5 X 15 X 15 sized output. This output has been further concatenated with the second immediately following network with patch size of 4 X 15 X 15 as input. Thus, an output with size of 5 X 1 X 1 is produced from the second module containing 9 input planes. This output is probably represents the normal class along with the four kinds of tumors. The proposed five kinds of nexus architecture are as follows: linear, two-path, two-path linear, the inception, and the inception linear nexuses.

*3) Post-Processing*

The Morphological operators utilize erosion and dilation techniques across the segmented images' edges to increase the prediction accuracy.

The segmentation is assessed by using the parameters like specificity, sensitivity, dice similarity coefficient (DSC) [10]. All the metrics were taken into account to categorize the classes as the developing tumor, core tumor, and complete tumor. This proposed network generates a significantly impressive outcome for the developing and core tumors through BRATS 2013 and BRATS 2015 datasets. This is due to the identical intensities of edema and healthy tissues. Therefore, the contrast improving and intensity modeling techniques can be applied to differentiate the healthy tissues and edema.

## III. Brain Tumor Segmentation Using CNN

The over-fitting effect can be eliminated through deeper architecture using light weighted small 3 X 3 kernel Convolutional neural networks (CNN) based automatic segmentation [1]. This could be accomplished in three steps, which are as follows: preprocessing, classification via CNN, and post processing

*1) Preprocessing*

Since the accuracy of the segmentation is affected by the variability in the contrast and intensity values of MR images sequence, this could be eliminated by normalizing the intensity [17]. In this technique, each and every sequence will be normalized and extracted as a patch individually to have a similar intensity and contrast ranges across all patients. The accuracy is improved by computing the intensity values and its standard deviation of all the extracted patches followed by normalizing the each sequence of the patches to attain the zero mean and unit variance.

*2) Convolutional Neural Network (CNN)*

CNN consist of several convolutional layers which were used to extract features from the input image. The following context is important for CNN,

**Initialization:** Xavier initialization [15] is used to achieve convergence.

**Activation Function**: Rectifier linear units (ReLU) is used and it is responsible transforming the data non- linearly.

**Pooling**: Nearby features in the feature maps are combined using Max Pooling

**Regularization**: Dropout [16], [17] were used in the FC layers. Drop out was done with probability P at each training step in order to reduce overfitting.

**Data Augmentation**: It was used to increase the size of training sets and to reduce overfitting [26].New patches are generated to increase the dataset by rotating of the original patch by using multiples of 90 degree angle.

**Loss Function:** Categorical Cross-entropy function was used. It is the function to be minimized during training

**Architecture**: Different architecture for HGG and LGG has been used. The architecture used for HGG is deeper than the one for LGG. Detailed description of the architecture is shown in [11].

**Training**: Stochastic Gradient Descent as an optimization algorithm is used.

*3) Post-Processing*

There can be some error in classification process and small clusters may be classified as tumor. Clusters with threshold smaller than predefined threshold are removed in order to deal with errors.

BRATS 2013 and 2015 were the two dataset used. The proposed architecture was evaluated with several different values for key components and it was found that the CNN with some specified component values shown in [11] provides good performance and reduces the time taken for segmentation.

## IV. One Pass Multiple Task CNN For well organized Segmentation of brain tumor

Single pass deep model for brain tumor segmentation was proposed to solve the problem of imbalance during classification. The segmentation task was divided into three tasks such as;

1. *Revealing the tumor completely using Coarse method of segmentation*

In this task, the network was trained with patches which are gathered at random from the brain for five-class segmentation problem. The network locates the entire tumor cells in the brain.

2. *Perceiving the whole tumor cells and its intra classes using Refined method of segmentation*

The mask of the tumor received from the previous task is prolonged by 5 vowels. Here the network is trained with patches which are collected around the prolonged ground-truth space of all tumors. Then, the task is to predict the class of all vowels in the prolonged region.

3. *Precise method of segmentation for enlarged tumor*

The network was trained with patches which are extracted at random from the ground-truth space of tumor core. It is trained to segment enlarged tumors.

*One Pass Multiple-Task deep model network*

Network architecture is identical for all the tasks excluding the last convolutional layer. Though Model Cascade (MC)-based segmentation framework [18,19] train each task individually and provides good performance , it suffers from system complexity. So One Pass Multiple-Task deep model network(OPM-DNN) was proposed to train these related tasks together to exploit their correlation and also facilitate the inference technique by one-pass computing since difference lies only in training data. In OPM-DNN, each task is provided with three layers such as a convolutional layer, a classification layer, and a loss layer, but the parameters of the model is shared by all the tasks. So in a single pass the predictions result of the three classifiers can be received all at once.

*Curriculum Learning*

Curriculum learning – based training [20] strategy was used to train the multitask model effectively which improves the convergence quality. First OPM-DNN was trained with the first task until it grasps all the underlying knowledge for categorizing tumor and normal tissues then the second task was concatenated with the first task sharing model parameter and training data then the third task was concatenated with the second and thus OPM-DNN captures the predictions of all the tasks as a whole by reducing the system complexity. At last post processing was done to get final segmented image with less error.

BRATS 2015 and 2017 were the two dataset used. Based on the table shown in [12] Dice Score value for OMNET model is greater when compared to MC model. Hence it performs better when compared to MC model.

## V. Brain tumor segmentation based on statistical thresholding and multiscale CNN

Brain tumor segmentation method proposed in [13] was based on statistical threshold and Multiscale Convolution Neural Network (MSCNN). Each patient has 4 modal MRI images. First the image preprocessing is done with the help of median filter. MRI images are first rougly segmented with statistical threshold [21] and produces small neighbourhood of the four model images (2D multi-modality MRI Images) as a result.

*Statistical Thresholding*

Each pixel of MRI brain tumor image has specific gray value and it varies from normal tissue pixel to tumor pixel. Based on this gray value statistical threshold method is used to segment the brain tumor from MRI images. This method consists of two steps. First smoothing of images are done by non-linear smoothing algorithm to diminish the impact of noise and artefacts on the image. Second step is to extract the tumor area by using statistical threshold.

There are L distinct gray levels (0, 1, 2…L-1) for each pixel of a given image. Each pixel is classified into two classes c1 and c2 based on the threshold t*[11]. Any pixel with threshold less than t* is classified as c1 and above the threshold is classified as c2. The variance of the two classes is calculated. Based on the variance t* value is changed between 0 and L-1.As a result 2D MRI images are obtained.

In this paper, MSCNN[22] was designed in such a way that four 2D MRI Images is given as input at the same time. There, the input images were passed through convolution layer, down sampling layers, fully connected layer and softmax classification layer. The features of the image such as the edges, texture of the tumor were obtained in convolutional layer through a convolution operation. The feature image which was acquired from convolution layer was resampled in the down sampling layer in order to reduce the amount of data processing by retaining important feature information.

The relationship between the output features were captured using fully connected layers. The extracted features were flattered and it was given as input to the softmax classifier which is the last layer of MSCNN. The classifier will classify each pixel in the image into two categories tumor and normal brain tissue with probability values. In this network, sigmoid transfer function and stochastic gradient method was used to minimize loss function. The segmentation binary image of the brain tumor undergoes a morphological post-processing operation to obtain the final segmentation result.

This method had a Dice coefficient of 86.3%, a PPV coefficient of 88.6%, and sensitivity coefficient of 85.2% on BRATS 2015 dataset. The proposed algorithm provides greater performance metric values and segmentation accuracy compared to other techniques such as SVM, Softmax Regression, Graph Cut.

## VI. AUTOMATIC SEGMENTATION OF BRAIN TUMOR USING END TO END INCREMENTAL DNN

In [4] End-to-End Incremental DNN models such as 2CNET, 3CNET, Ensemble Net is developed. "Incremental XCNet" algorithm was proposed in [14] generates deeper and scalable 2CNET and 3CNET Model. Then ensemble learning technology was used to merge 2CNET and 3CNET model to produce Ensemble Net model for automatic Brain Tumor Segmentation with higher accuracy.

### *Incremental XCNet and ELOBA Algorithm*

MRI is the investigation tool for brain tumor segmentation. For a particular patient, MRI generates 4 sequences of images such as Flair, T1, T1c, T2. These images are used to extract size, shape, and volume of the tumor in the brain. From the previous works it is identified that 32* 32 Pixel size images will produce accurate result so 4 MRI images of a particular patient (4*32*32) is given as input to Incremental XCNet algorithm.

Set of convolution and pooling layers is called as bloc. Initially base model called as bloc is created with fixed number of convolution and pooling layers. In [14] it is taken as 2 convolution layers and 1 pooling layer. Then this base model is trained with the ELOBA algorithm [14] to adjust the weights till it learns all the new features from the given input. The ELOBA algorithm includes the parameters such as Learning rate, Epoch, Batch size.

Dice Coefficient is initialized with 0.Then the Dice coefficient value is calculated for each iteration. When the value of Dice Coefficient for the current iteration is better than the previous iteration then the model is stored and continued with training for next set of epochs. Hyper parameter values were tuned in order to improve the accuracy of the system. If the value of Dice Coefficient is not improved then the architecture is altered by adding another bloc and checked for accuracy. Hence the architecture of the CNN is based on the training algorithm where as in other techniques the CNN architecture is predefined before training.

Both 2CNET and 3CNET was constructed using "Incremental XCNet" algorithm[14]. Both models produce complete predicted images and the next step is to combine these two images using non parametric fusion function [14] to get more accurate image as final result using ENSEMBLE NET Model

BRATS 2017 Data set is used in this approach. Relevant and high level features are extracted using proposed models such as 2CNET, 3CNET and Ensemble Net. These models produce high accuracy with less inference time when compared to normal CNN models.

## VII. CONCLUSION

Segmentation of the brain tumors automatically for cancer diagnosis is a challenging task. In this paper, a review of the state-of-the-art methods based on deep learning is provided. Even Convolution Neural Network can automatically extract complex features from the images. Further improvements and modifications in CNN architectures and addition of complementary information can improve the efficiency of segmentation.

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