3D Brain Tumor Segmentation Using Deep Learning

M.S.R.Naidu[1], B.V.Srivani[2], Y.R.L.V.D. Bhavani[3]

[1] *Associate Professor, Department of ECE, Aditya Institute of Technology And Management, Tekkali-532201*

[2,3] *UG Scholar, Department of ECE, Aditya Institute of Technology And Management, Tekkali-532201*

Abstract: *Brain tumor segmentation plays an important role in medical image processing. Treatment of patients with brain tumors is highly dependent on early detection of these tumors. Early detection of brain tumors will improve the patient's life chances. Diagnosis of brain tumors by experts usually use a manual segmentation that is difficult and time consuming because of the necessary automatic segmentation. Now a days automatic segmentation is very popular and can be a solution to the problem of brain tumor segmentation with better performance. Deep learning methods can also enable efficient and objective evaluation of the large amounts of MRI-based brain tumor image segmentation. In this paper, we propose an automatic segmentation method based on Deep Learning Techniques. By using this method, the chances of survival of a tumor-infected patient can be increased significantly if the tumor is segmented accurately in its early stage.*

Keywords: Tumor, Segmentation, Deep learning, MRI,

1. INTRODUCTION

In digital image processing and computer vision, image segmentation is the process of partitioning a digital image into multiple image segments, also known as image regions or image objects (sets of pixels). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain characteristics.

The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image. Each of the pixels in a region are similar with respect to some characteristic or computed property , such as color, intensity, or texture. Adjacent regions are significantly different color respect to the same characteristic(s). When applied to a stack of images, typical in medical imaging, the resulting contours after image segmentation can be used to create 3D reconstructions with the help of interpolation algorithms like marching cubes.

The brain tumor is an abnormal growth of uncontrolled cancerous tissues in the brain. A brain tumor can be benign and malignant. The benign tumor has uniformity structures and contains non-active cancer cells. The malignant tumor has non-uniformity structures and contains active cancer cells that spread all over parts. Depending on their initial origin, brain tumors can be considered as either primary brain tumors or metastatic brain tumors. In primary ones, the origin of the cells are brain tissue cells, where in metastatic ones cells become cancerous at any other part of the body and spread into the brain. Many different types of primary brain tumors exist.

2. Literature Study

Analyzing and processing of MRI brain tumor images are the most challenging and upcoming field. Magnetic resonance imaging (MRI) is an advanced medical imaging technique used to produce high-quality images of the parts contained in the human body and it is very important process for deciding the correct therapy at right stage for tumor-infected individual. Many techniques have been proposed for classification of brain tumors in MR images such as fuzzy clustering means (FCM), support vector machine (SVM), artificial neural network (ANN), knowledge-based techniques, and expectation-maximization (EM) algorithm technique which are some of the popular techniques used for region-based segmentation and so to extract the important information from the medical imaging modalities. Bahadure et al. proposed BWT and SVM techniques image analysis for MRI-based brain tumor detection and classification. In this method, accuracy of 95% was achieved using skull stripping which eliminated all non-brain tissues for the detection purpose [1]. Joseph et al. [2] proposed segmentation of MRI brain images using K-means clustering algorithm along with morphological filtering for the detection of tumor images. The automated brain tumor classification of MRI images using support vector machine was proposed by Alfonse and Salem [3]. The accuracy of a classifier was improved using fast Fourier transform for the extraction of features and minimal redundancy maximal relevance technique was used for reduction of features. The accuracy obtained from this proposed work was 98%.

The brain MRI image contains two regions which are to be separated for the extraction of brain tumor regions. One part of region contains the tumor abnormal cells, whereas the second region contains the normal brain cells [4]. For the brain tumor segmentation, Zanaty [5] proposed an approach based on hybrid type, with the combination of seed growing, FCM, and Jaccard similarity coefficient algorithm with the measure of gray and white segmented tissue matter from tumor images. An average score of S of 90% segmentation was achieved with noise level of 9–3%. To manage and to address protocols of different images and nonlinearity of real data an effective classification based on contrast of enhanced MRI images, Yao et al. [6] proposed an methodology which included extraction of textures features with wavelet transform and SVM with an accuracy of 83%. For the classification and brain tumor segmentation, Kumar and Vijayakumar [7] proposed methodology using principal component analysis (PCA) and radial basis function kernel with SVM. They obtained an accuracy of 94% with this method. An artificial neural network tool as both classifier and segmentation was used for the effective classification of brain tumor from MRI images was proposed by Sharma et al. [8] with the utilization of textural primitive features which achieved an accuracy of 100%.

For the medical image segmentation, a localized fuzzy clustering with the extraction of spatial information was proposed by Cui et al. [9]. The author used Jaccard similarity index as a measure of segmentation claiming an accuracy of 83–95% and differentiating in to white, gray and cerebrospinal fluid. For the brain tumor image segmentation, active contour method was applied to solve the problem based on intensity homogeneities on MRI images was proposed by Wang et al. [10]. For the automatic extraction of features and tumor detection a with an enhanced feature using Gaussian mixture model applied on MRI images with wavelet features and principal component analysis.

3. SUPERVISED LEARNING

In supervised learning training process, during the training process we give both input and the output. For example teacher shows a photograph to a child saying it a dog this is called a supervised learning. In supervised learning, we provide labeled data to system like this is the input, this is the output, this is the background and this is the tumor. The data we provide is called ground truth data. Based on that we can tell that the particular pixel belongs to tumor and particular pixel belongs to the normal data. Based on the data provided, the system classifies.

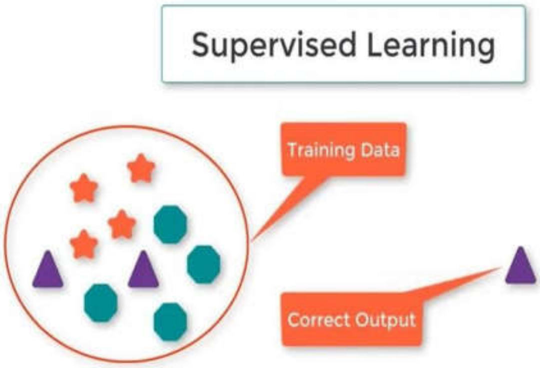

Figure 1: Supervised Learning

The step 1 includes initializing the weights based on the random method and the step 2 is calculating the error. The equation for error is given as follows:

ei = di - yi

Where ei = error, di = correct output, yi = output

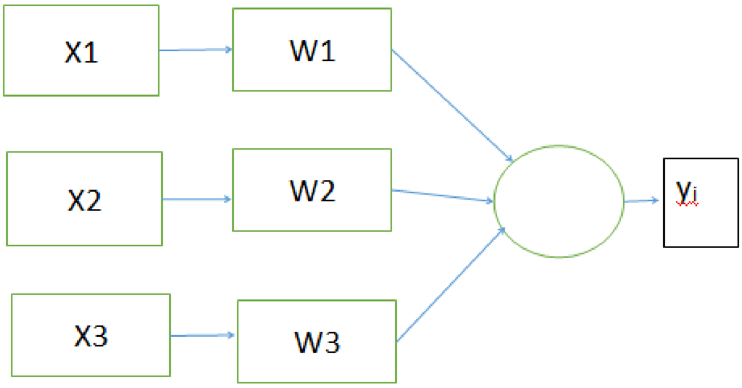

Figure 2: Step 2

Δ wij = αeixj

wij← wij + δ wij

Step 2 to 4 has to be repeated for all the images for training process. So step 2 to 4 are called an One Epoch and it should be repeated to all the images.

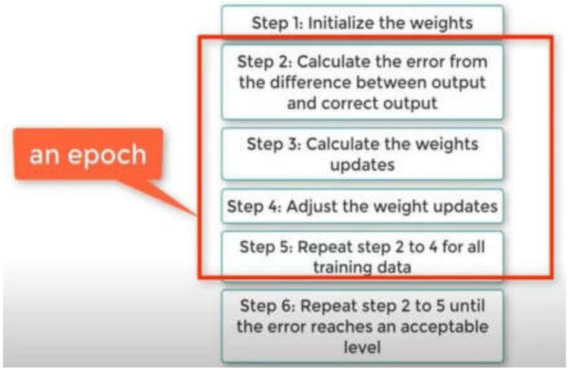

Figure 3: Step 3

We can have any number of epochs. Step 6 is repeating step 2 to 5 for getting accuracy that means until the error reaches a acceptance level. For updating weights we have the following methods:

1) SGD Method
2) Batch Method
3) Mini Batch Method

Stochastic Gradient Descent Method

Figure 4: Stochastic Gradient Descent Method

Stochastic gradient descent is an iterative method for optimizing an objective function with suitable smoothness properties. In Stochastic Gradient Descent, a few samples are selected randomly instead of the whole data set for each iteration. In this method wait is updated N times in each epoch.

Batch Method

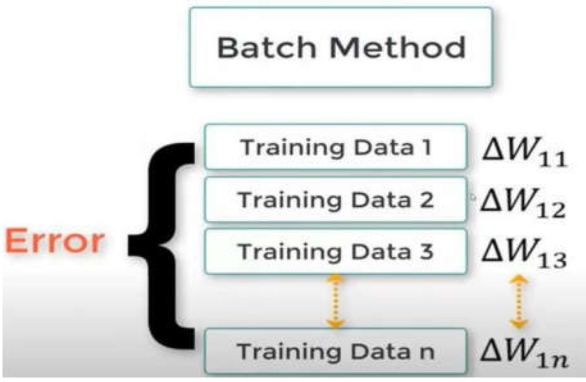

Figure 5: Batch Method

In batch mode, for all samples in the training set, we calculate the error, delta and thus delta weights for each neuron in the network and then instead of immediately updating the weights, we accumulate them, and then before starting the next epoch, we update the weights. Weight is updated only once in each epoch.

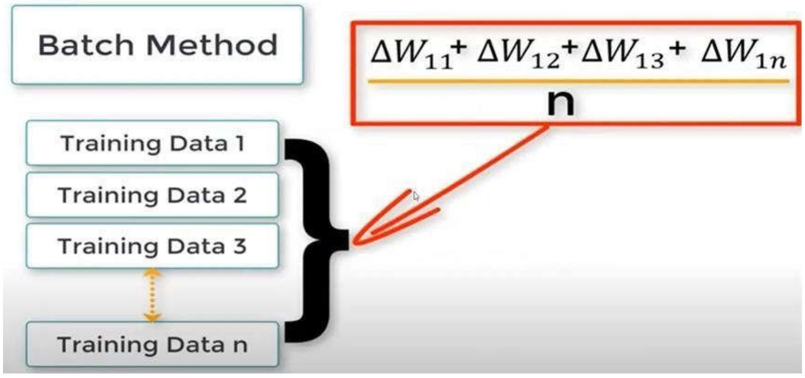

Figure 6: Batch Method for all samples

It uses average method. Because of average method the training takes long time in batch method.

Mini Batch Method

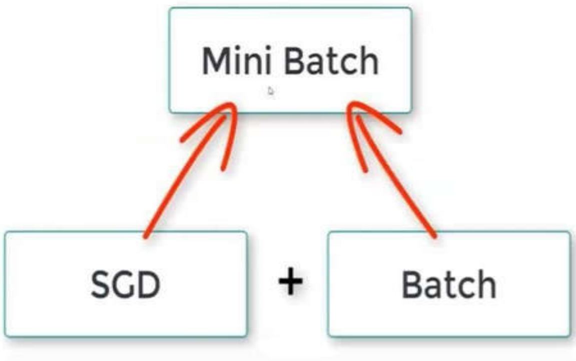

Figure 7: Mini Batch Method

Mini batch method is combination of stochastic gradient descent method and batch method. It has the speed of SGD method and stability of Batch method. It is widely used method. In our process we use mini batch method.

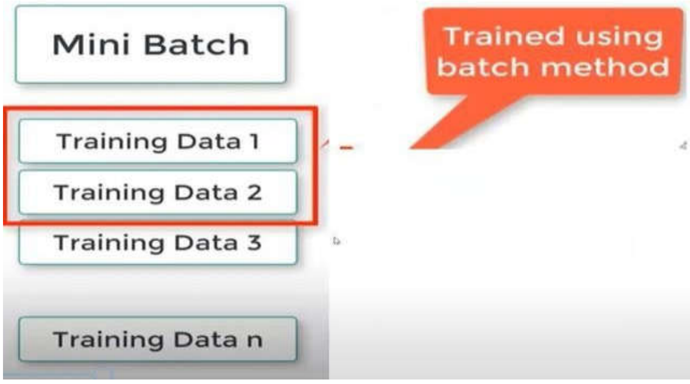

Figure 8: Mini batch method training

Deep learning has automatic feature extraction. It provides both input and ground truth data to the system which is necessary for classification. In machine learning we need to do that manually and if we choose a wrong feature extraction we may get the wrong output. In deep learning feature extraction is done automatically but building the neural network is a complex thing. Machine learning will work even with a less number of data but deep learning we need more number of images for training sometimes in labels. In 3D brain tumor segmentation we need to take the ground truth for at least one lakh and then we need to train the images which take a lot of time but makes the medical analysis easy.

Since, 3D image processing is commonly used in medical imaging to analyze DICOM or NIfTY images from radiographic sources like MRI or CT scans. You can also use 3D image processing techniques in microscopy to detect and analyze tissue samples or trace neurons. DICOM format of images is mostly meant for medical imaging. Image always stores in a binary format. For DICOM they store 16 bit of data for a pixel. The way the DICOM arrange the pixel is also different. For 3D image processing, we could slice the top view, side view and front view and get information. We call this as sampling. When we cut the slice we get a matrix. More cuts give more samples. When we get more samples it gives us the more information and it also takes more data to store. It also takes more time for data process for example; if we cut 4 slices we get 4 samples.

Block Diagram

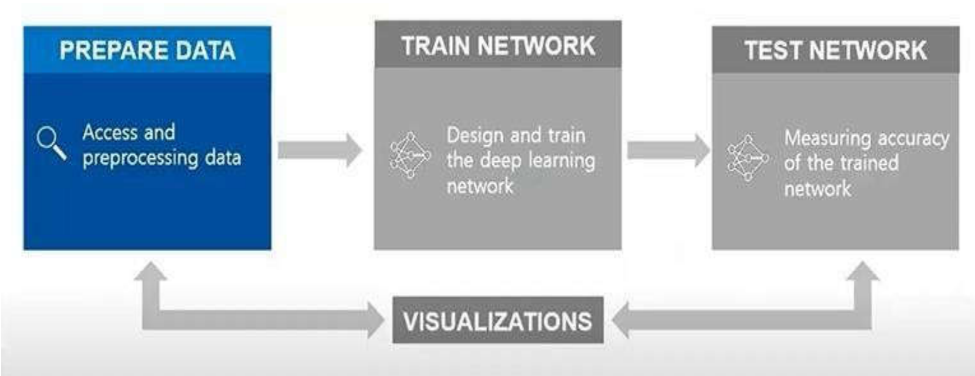

Figure 9: Block Diagram

The first step in this block diagram shows that preparing and accessing the data. This is the ground truth data since we are using a supervised learning it is a ground truth data, here we need to provide both Input and the ground truth training process but we need doctor to tell whether it is a tumor cell or a normal cell. We read data using image store. After reading we split the label for training, validation and testing data. And then before applying training extract pixel data. We are using data by from the medicaldecathlon.com. It is a research group for medical image segmentation.

The second step is to train the network. Before the training construct/design the neural network. We set the hyper parameters in train network. We use the network layers like input 3D layer, convolution 3Dlayer, batch normalization layer, softmax layer, concatenation layer. Before testing the network for accuracy in pre process training and validation data we crop the data to a region containing primarily the brain and the tumor cropping the data reduces the size of the data while retaining the most critical part of the MRI volume and its corresponding labels. We normalize each modality of each volume independently by subtracting the mean and dividing by the standard deviation of the cropped brain region and split the data set into training, validation and test sets. For example, if we have 100 images it takes 70 images for training, 15 images for validation and 15 for testing. So, it takes 82% of images for training 6% of images for validation and 12% of images for testing. This paper has 484 training volumes which split into 400 training, 29 validations and 55 test sets. These gives the output of both ground truth labeled volume output and network prediction labeled volume output and we can see the accuracy of the tumor and also the background.

4. Results & Discussion

Demonstration of the process of finding a part of the tumor in each slice by comparing the ground truth and network. Since we are using supervised learning the data is trained earlier. So that, the given data and the trained data will used in identifying the tumor containing slice. Here in the results it can be concluded that the ground truth and network are used to load volume and load the label and these are depicted below. The test set dice accuracy is used to measure the tumor levels in the brain.

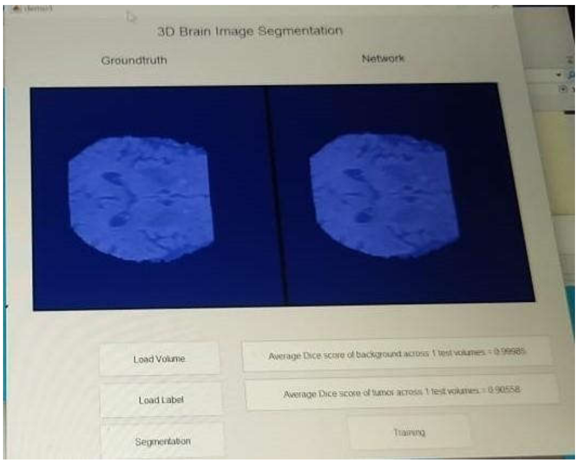

Figure 10: Loading volume & Label

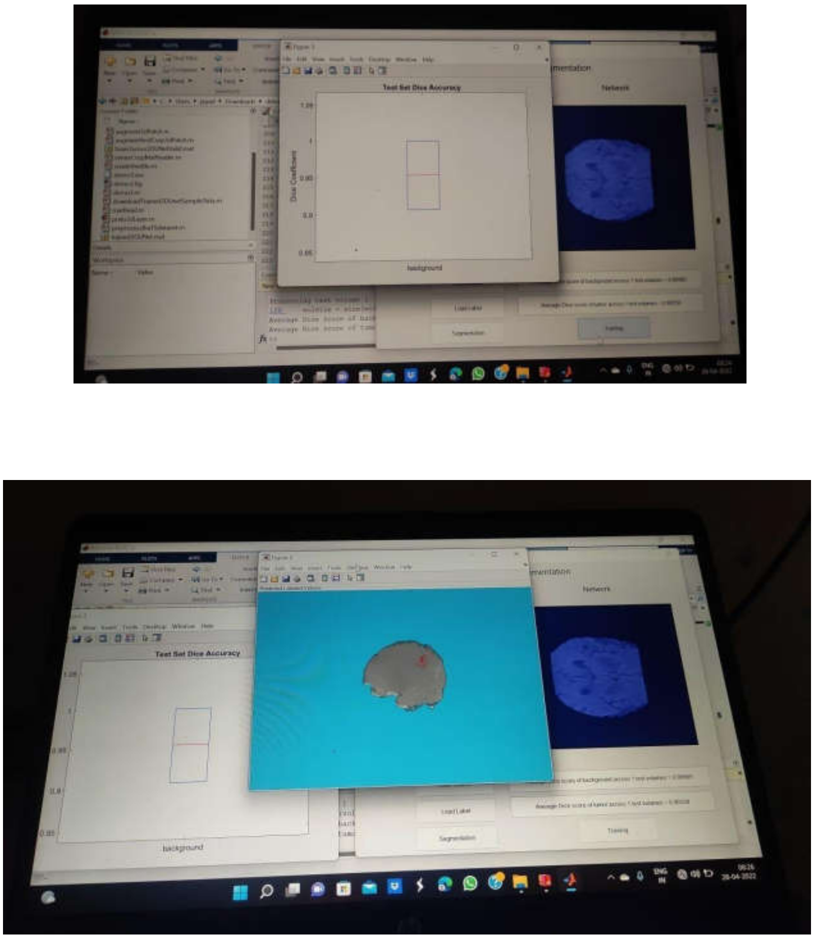

Figure 11: Dice accuracy

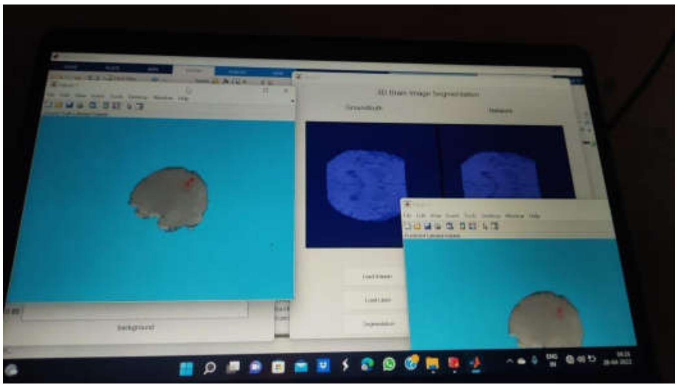

Figure 13: 3D Brain image segmentation

5. Conclusion

In this paper, we have developed a new brain tumor segmentation architecture that benefits from the characterization of the MRI modalities. It means that each modality has unique characteristics to help the network efficiently distinguish between classes. We have demonstrated that working only on a part of the brain image near the tumor tissue allows a CNN model (that is the most popular deep learning architecture) to reach performance close to human observers. Moreover, a simple but efficient cascade CNN model has been proposed to segment the MRI images for determining the affected tumor part using imaging modalities with the accuracy of 99 percent. This method leads to reducing the computational time and capability to make predictions fast for classifying the clinical image as it removes a large number of insignificant pixels off the image in the preprocessing step. Results show accuracy of overall 100% for validation and testing and for identifying the background and tumor it shows 99% accuracy.

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