BRAIN TUMOR DETECTION USING MASK R–CNN

[1]S. DEEPIKA, [2]A.SRAVANTHI PEDDINTI, [3]J. STELLA MARY

Abstract: *Brain MRI segmentation is an important task in many clinical applications. Various approaches for brain analysis rely on accurate segmentation of anatomical regions. Quantitative analysis of brain MRI has been used extensively for the characterization of brain disorders such as Alzheimer's disease, epilepsy, schizophrenia, multiple sclerosis (MS), cancer, and infectious and degenerative diseases. Manual Segmentation requires outlining structures slice-by-slice, and is not only expensive and tedious but also inaccurate due to human error. Not only that, segmentation is extremely time-consuming and initial hours of brain tumor and strokes are crucial to diagnosing. Therefore, there is a need for automated segmentation methods to provide accuracy close to that of expert ratters' with high consistency. We propose to create a Deep Learning based Brain Segmentation web application that would fully automate the process of Brain Segmentation to help in solving out those cases which are generally missed by the human eye and save time.*

Keywords:- *Mask R-CNN, Brain Tumor, medical, deep learning, python, magnetic resonance imaging, image segmentation.*

I. INTRODUCTION

Brain Tumor is an abnormality growth arising from the brain tissues, which could be life threatening if not detected and appropriately treated at an early stage. Typically, Magnetic resonance imaging (MRI) and Computer Tomography (CT) scans are used by medical staff to obtain detailed images of the brain for initial analysis, over invasive procedures such as tissue biopsies. Further, use of computer-based image analysis in collaboration with medical knowledge, can contribute significantly to aid the early diagnosis [2]. Hence, increasing number of existing and new computer-based image classification and segmentation algorithms are applied and validated in this line of study by many researchers [1-3, 5-7]. The accurate segmentation of gliomas and its intra-tumoral structures is important not only for treatment planning, but also for follow-up evaluations. However, manual segmentation is time-consuming and subjected to inter- and intra-rater errors difficult to characterize. Thus, physicians usually use rough measures for evaluation. For these reasons, accurate semi-automatic or automatic methods are required. However, it is a challenging task, since the shape, structure, and location of these abnormalities are highly variable. Additionally,

[1] Assistant Professor, Department of ECE, Bhojreddy Engineering College for Women
[2] Sr. Assistant Professor, Department of ECE, Aditya College of Engineering and Technology
[3] Assistant Professor, Department of ECE, Bhojreddy Engineering College for Women

the tumor mass effect change the arrangement of the surrounding normal tissues. Also, MRI images may present some problems, such as intensity inhomogeneity, or different intensity ranges among the same sequences and acquisition scanners.

Image classification and segmentation has been studied for many years with several different types of algorithms, in image processing and computer vision, for supervised, unsupervised feature extractions. Recently, CNN has become the most popular approach for image segmentation and classification in different areas of research, such as medical imaging, video surveillance, factory automation, etc.[2] to achieve automation. The foremost appeal of CNN is its ability to learn increasingly complicated features from the input for the classification task. For instances, architectures of CNN such as, Alex Krizhevsky network (AlexNet) is a popular choice in medical image segmentation [3], whereas GoogLeNet and ImageNet are extensively used in visual recognition, and computer vision[4]. However, applications of CNN was restricted in the past decade due to the computational cost and the training time associated with the system architecture. But recently, with the advancements of modern computing technologies, specifically Graphics Processing Unit (GPU), the performance of CNN has improved drastically with significant reduction in processing time.

II. METHODOLOGY

i) Introduction to Convolutional Neural Network

In the normal neural network, image cannot scalable. But in convolution neural network, image can scalable (i.e) it will take 3D input volume to 3D output volume (length, width, height).The Convolution Neural Network (CNN) consists of input layer, convolution layer, Rectified Linear Unit (ReLU) layer, pooling layer and fully connected layer. In the convolution layer, the given input image is separated into various small regions. Element wise activation function is carried out in ReLU layer. Pooling layer is optional. We can use or skip. However the pooling layer is mainly used for down sampling. In the final layer (i.e) fully connected layer is used to generate the class score or label score value based on the probability in between 0 to 1.

CNN is a layered architecture which performs convolution, activation, pooling, and fully connectedness to analyze visual imagery. The main improvement of CNN from the traditional artificial neural network (ANN) is the convolution layer. The primary purpose of convolution is to extract features from the input images. In the convolutional layer, the model uses different kinds of filters of different sizes to build various feature maps. By introducing this layer, the model will drastically reduce the number of weighted parameters. Also by convolutional technique, the network is able to learn the correlations between the neighboring pixels [8].

As the first step, input images are fed to the model and the dot product is applied to the input image and parameter vectors of each neuron. Then convolution operator is applied to each input at each convolutional layer. To keep the size of output array unchanged, the system utilizes zero padding in the edges. Furthermore, activation functions are introduced after the convolution, to enhance the system performance in comparison with a linear model. It is well known fact that the rectified linear unit(ReLU) given in(1),minimizes computations as well as increases the training speed, compared to activation functions such as sigmoid, tan hyperbolic. Hence, CNN employs ReLU as its activation function

$$Relu(x) = \begin{cases} 0 & if\ x < 0 \\ x & if\ x \geq 0 \end{cases} \quad (1)$$

The pooling layer of CNN basically reduces the dimensionality of each feature map without the loss of predominant information. Pooling layer will perform a down sampling operation along the spatial dimensions which results in a decrease in computation. After that, the output is computed using loss function and output of the model is compared with desired values. Then the back-propagation technique is applied to estimate the error. These four operation; convolution, activation, pooling and back-propagation, are repeated in CNN architecture to gain a better accuracy.

Algorithm for CNN based Classification

1. Apply convolution filter in first layer
2. The sensitivity of filter is reduced by smoothing the convolution filter
3. The signal transfers from one layer to another layer is controlled by activation layer
4. Fasten the training period by using rectified linear unit (RELU)
5. The neurons in proceeding layer is connected to every neuron in subsequent layer
6. During training Loss layer is added at the end to give a feedback to neural network

ii) Faster Region based-Convolutional Neural Network

Faster Region based-Convolutional Neural Network used as a classifier which trains CNNs to classify proposal regions into object categories or backgrounds. Region proposal network (RPN), outputs a set of rectangular object proposals, from the input image using fully convolutional network. The R-CNN and RPN are two main networks which are used in faster R-CNN. The main distinction of faster R-CNN is it uses selective search to generate region proposals compared to other CNN algorithms. The main insight of Faster R-CNN was to replace the slow selective search algorithm with a fast neural net [9], [10].

The RPN generates anchors, i.e. region boxes, using the input image. The RPN predicts the probability of an anchor being background or foreground and anchors with maximum number of region proposal is selected as the desired proposals. It improves region proposal quality and overall object detection accuracy [11]. The challenge is to label the anchors having the higher overlaps with ground truth boxes as foreground, lower overlaps as background. Therefore every anchor represents itself either as foreground or as background with the label of the prediction [12].

NMS (Non Maximum Suppression) are used to find the exact location of tumor. To find correct location of the object, it is needed to merge the ROI that can be done by NMS.

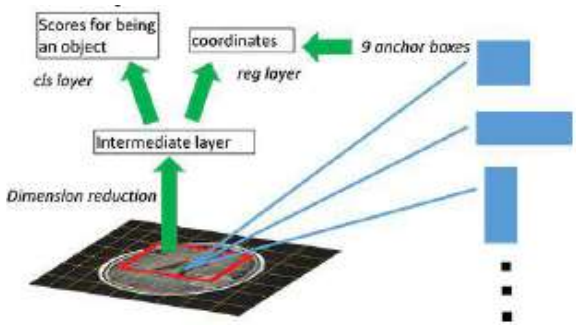

Fig1: Region proposal network

NMS identify the tumor by selecting high confidence region of interest and discard the remaining ROI that overlaps the same class this ROI belongs. Brain tumor detection results before and after NMS are shown in fig 2. After training the model, the quality of model can be measured using various criteria here Average Precision (AP) are used for each class. Taking the overall average of AP for all 4 classes are called Mean Average Precision.

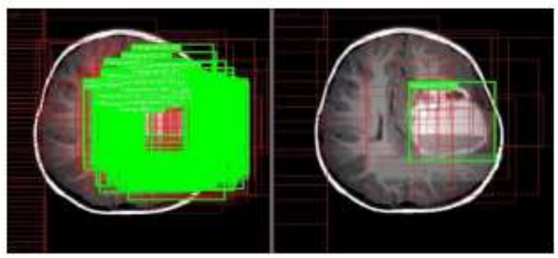

Fig. 2. Bounding box before NMS and after NMS

The CNN model employed is based on [13] and only minimal preprocessing is used to avoid information loss and to retain the useful features of the MRI dataset. At the preprocessing stage, the input image is down sampled to 128x128 image and fed into the CNN model as shown in the Fig.2.It must be noted that due to down sampling the sensitivity of the output could be reduced by a small fraction, as some features of the input could be lost during the process, Since the input images are in uint8 format, pixel values of all the images are divided by 255 to normalize. Therefore the pixel values of normalize images are in the range of 0-1.

The proposed system consists of two stages; training and testing. The model is trained using 218 images of two tumor types, meningioma and glioma, and tested with another dataset which is independent from training dataset [11]. The proposed architecture of the working model is shown in Fig.2. This architecture comprise of pre-processing for dimension reduction, CNN model for feature extraction and tumor classification, and finally faster R-CNN model for tumor extraction. In mathematics the convolutional procedure can be expressed as (2),

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$$Yi^{l+1}\,j^{l+1},d = \sum_{i=0}^{128}\sum_{j=0}^{128}\sum_{d=0}^{D} f_{i,j,d} \times X^{l}_{i^{l+1}+i,\,j^{l+1}+j,d}$$

As shown in Fig 2, first the normalized dataset is fed to the1st convolutional layer. The over-fitting was reduced, with the normalization techniques employed in the system architecture, at the 1st convolutional layer, the input images are convolved with 20 filters each with 3×3 size kernels, and creates 20 different feature vectors [15]. In general, 20 feature maps were sufficient at the first layer, to gain a sufficient accuracy. Then the output of this layer is fed to ReLU and maxpool layers with 2×2 window size.

The 2nd Convolutional layer also consists of 10 filters having 3×3 kernel size. As in the previous layer, the output of the convolution layer is fed to activation function (ReLU) and maxpool with 2×2 window size. The output at this stage will have 10 feature vectors. It was observed that, 10 feature vectors are sufficient at this stage to achieve a good level of overall performance. The purpose of using max pooling layer is to reduce the dimension by interpreting the maximum value of the window [13]. Then it converts 2D feature maps to 1D feature vectors by flattening. For the classification task, it is used as a fully connected layer and output layer output the decision, whether the input is a meningioma or glioma.

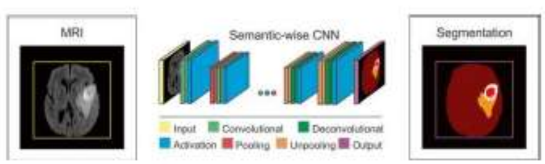

Fig3: Proposed Network

III. RESULTS AND DISCUSSION

We will be using the Mask R-CNN framework created by the Data scientists and researchers at Facebook AI Research (FAIR).

Let's have a look at the steps which we will follow to perform image segmentation using Mask R-CNN.

Mask RCNN has been the new state of art in terms of image segmentation. There are rigorous papers, easy to understand tutorials with good quality open source codes around for your reference. Here I want to share some simple understanding of it to give you a first look.

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Fig no 4: Mask R-CNN

There are two stages of Mask RCNN. First, it generates proposals about the regions where there might be an object based on the input image. Second, it predicts the class of the object, refines the bounding box and generates a mask in pixel level of the object based on the first stage proposal. Both stages are connected to the backbone structure.

Instance Segmentation:

Instance segmentation is the task of detecting and delineating each distinct object of interest appearing in an image.

Mask Regional Convolutional Neural Network (R-CNN) is an extension of the faster R-CNN object detection algorithm that adds extra features such as instance segmentation and an extra mask head. This allows us to form segments on the pixel level of each object and also separate each object from its background.

Instance Segmentation is task of detecting and describing the each object in the given image. It treats multiple objects of same class as distinct individual objects shown in the above image.

Semantic Segmentation:

Semantic segmentation treats multiple objects of same class as single entity. It is different from Instance segmentation.

To understand the difference between instance segmentation and Semantic Segmentation easily let’s follow this image.

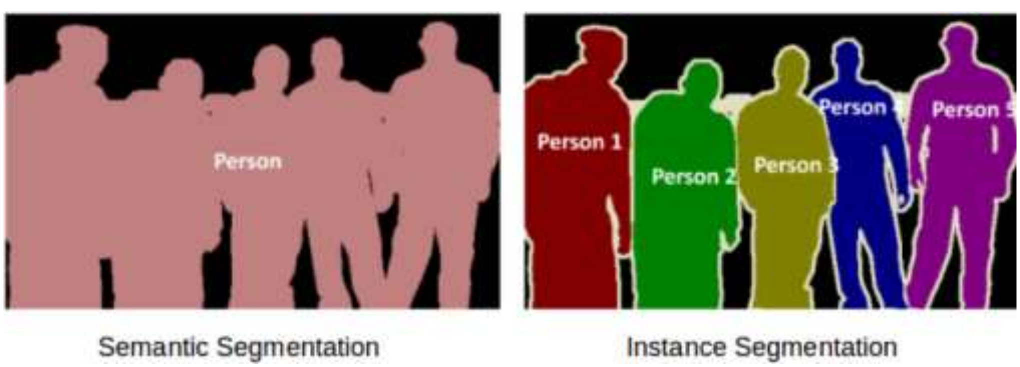

Fig no 5: Difference between Semantic and Instance Segmentation

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Semantic segmentation considers different objects and produce single mask to all the objects. While Instance Segmentation considers different objects as different entities and produce mask to different objects separately and label them.

Data

The data we used in this project is the image data. The images are MRI scan images. The images are grayscale images.

- Data set has lot of duplicate scans which tried to remove.
- The images are resized by cropping the extreme points of the images and crops the rectangular of them.
- Image annotation is also carried out using VGG image annotator (VIA).

Data set before resizing looks something like this.

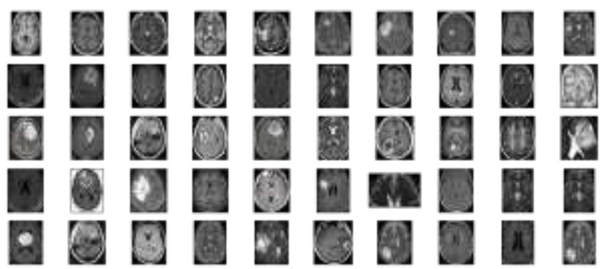

Fig no6: Image data before resized

After resizing the images the data looks something like this.

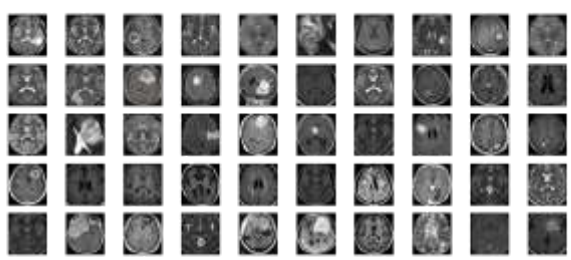

Fig no 7: Resized image data

After the duplicate images are deleted and resized the data is stored in a different folder. The data is divided into three different folders Train, Test and Validation folders.

Since we're using a very small dataset, and starting from COCO trained weights, we don't need to train too long. Also, no need to train all layers, just the heads should do it.

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Dataset class also supports loading multiple data sets at the same time. This is very helpful when you want to detect different objects and they are all not available in one data set.

Based on the MRI scan images this project is carried out. The obtained result of the project is a brain scan image in which the tumor area is been highlighted with Mask over it and boundary mask. The obtained accuracy by this project is pretty good. The Brain Tumor Detection using Mask R-CNN gave good results. Mask generated on the tumor is accurate. Deep Learning is a constantly evolving field and there is always room for improvement in your methodology. There is always going to be another new approach that gives better results for the same problem. The results obtained using Mask-RCNN is shown in the form of images. It is easy find the abnormal part in MRI scan images. The result is as shown in the below MRI scan image:

Fig no 8: Resultant image of the project

IV. CONCLUSION

This paper presents an overview about the Brain Tumor Detection using Mask R-CNN and how it is helpful in real time. I also provided the usage and working of commonly used CNN. I have provided the different steps of execution along with the detail approach which helped in finding the tumor in brain. This method still needs improvement such as implementing it on huge data. This can help in improving the overall accuracy even though this method is successfully detecting the tumor in the brain using the MRI scan images without any trouble. So, in the end our model can detect the brain tumor using Mask R-CNN without any errors. This work can help resolve interesting research challenges finding tumor more accurately.

Future work: Future work includes extension of this proposed approach for detecting different types of tumor in all parts of human body and to find the actual size of tumor.

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