



A NOVEL APPROACH FOR CLASSIFICATION OF BRAIN TUMOR USING R-CNN

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Abstract: In this study the problem of fully automated brain tumor classification and segmentation, in Magnetic resonance imaging (MRI) containing both Glioma and Meningioma types of brain tumors are considered. This paper proposes a Convolutional Neural Network (CNN), for classification problem and Faster Region based Convolutional Neural Network (Faster R-CNN) for segmentation problem with reduced number of computations with a higher accuracy level. An automatic segmentation method based on Convolutional Neural Networks (CNN), exploring small 3x3 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. This research has used 218 images as training set and the systems shows an accuracy of 100% in Meningioma and 87.5% in Glioma classifications and an average confidence level of 94.6% in segmentation of Meningioma tumors. The segmented tumor regions are validated through ground truth analysis and manual analysis by a Neurologist.

Keywords—Convolutional Neural Networks, Brain Tumor, Magnetic resonance imaging, Segmentation, Classification, Computer Vision

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 intratumoral 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, 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

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

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.

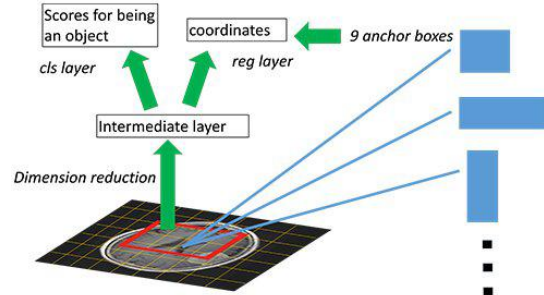


Fig1: Region proposal network

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.

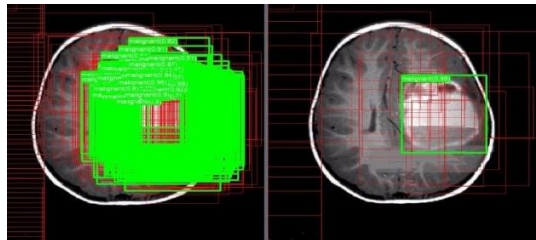


Fig. 2. Bounding box before NMS and after NMS

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),

$$Y^{i^{l+1} j^{l+1}, d} = \sum_{i=0}^{128} \sum_{j=0}^{128} \sum_{d=0}^D f_{i,j,d} \times X_{i^{l+1}+i, j^{l+1}+j, d}^l$$

As shown in Fig 2, first the normalized dataset is fed to the 1st 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 3x3 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 2x2 window size.

The 2nd Convolutional layer also consists of 10 filters having 3x3 kernel size. As in the previous layer, the output of the convolution layer is fed to activation function (ReLU) and maxpool with 2x2 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.

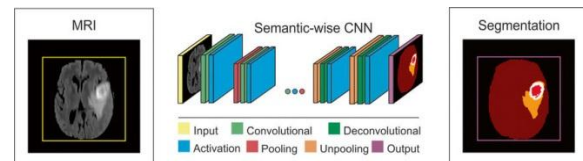


Fig3: Proposed Network

III. RESULTS AND DISCUSSION

After CNN classify the tumor as meningioma or glioma, faster R-CNN is used for tumor segmentation and localization. In our system, only the meningioma dataset is used for the segmentation. Yet, this model can be extended to the



gliomas dataset as well without loss of generality. The meningioma dataset was split into two; 110 images for training and 9 images for the validation. Here each region proposal consists of an “objectness” score for that particular region, and coordinates for the bounding box representing the region proposals.

At the last layer of the CNN, a 3×3 sliding window moves across the feature map and it maps to a lower dimension. The basic objective is to search each location in the last feature map, with search boxes of varying sizes and centered on the region of interest. Each region box gives the coordinates of the box and whether an object is present within it [14][16]. As in Fig.2, each bounding box, represents the softmax probability of encircling an object within its boundary. If an anchor has an object score above a certain threshold, the anchor coordinates get forwarded as a region proposal. Thus before proposing regions for the feature extraction, the system runs one full CNN over the full image and extend the neural network for prediction by softmax layer. The significance of this is, instead of training many different models to classify each object class, it outputs the class probabilities directly. Therefore it has only one neural network to train. Henceforth, the proposed architecture performs much better in terms of speed, since it only needs to locate the tumor area bounding box rather than classifying. Thus, the final output of the proposed model is the bounding box and the confidence level indicating the probability of the region box being [11] a meningioma.

The normalized coordinates of the bounding box are given as the output of the faster R-CNN model and these coordinates are with reference to the low resolution images (128×128). After detecting the coordinates of the bounding box, it is mapped to the image with original resolution (512×512) and obtain the estimated area of meningioma tumor.

Initially the accuracy of the proposed system was analyzed for the classification of meningioma and glioma tumors as shown in Table I. The two-layered CNN used for feature extraction and classification demonstrates a very accurate result in identifying the tumor type and extracting the tumor regions. According to the results presented in Table I, the proposed model was able to classify the two tumor types with a nearly 94% accuracy. Further, the detection accuracy of meningioma is 100%. These results were generated after running our proposed network on a data set of 218 images.



Fig4: Binary images for different threshold values

Moreover, the classification task is improved by segmenting the tumor regions from classified images. Table II presents the segmentation outputs of our system for selected images. The results were checked against ground truth pixel level labels generated by Neurologists. The original T1 images [17] of the meningioma tumors are shown in Table II under first row ‘T1 images’. These images were selected randomly from the validation dataset of meningioma tumors. These original images, which are of size 512×512, are down sampled to 128×128 to gain a high speed training process as well as to reduce the computational cost. Here it is noticed that none of the significant features are lost due to down sampling to this dimension. The second row of table shows the resultant images for the validation dataset after feeding them to the pre-trained model. The bounding boxes and confidence levels for each tumor are labeled in the images itself using our system. Next, it maps the low resolution output of the system to original resolution (512×512) to improve the clarity of the detection process. The Original resolution images with the bounding boxes are shown in the third row of Table II. Then it extracts the approximated tumor boundary within the relevant bounding boxes. For this purpose, Prewitt edge detection operator was applied only to the bounding box region.

Table 1: Result of the classification process

Classes	Meningioma	Glioma
Total No. of Images in Database	156	194
No. of images train CNN	124	154
Training Accuracy	100%	100%
No. of images tested	32	40
No. of Images classified Successfully	32	38
Test Accuracy	100%	95%

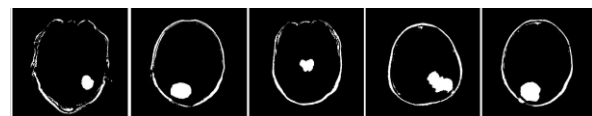


Fig5: Binary images of the tumor masks against rest of the images

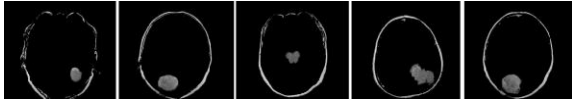


Fig6: Extracted tumor region against rest of the images

IV. CONCLUSION

This paper presents a CNN based unique mechanism to automate the brain tumor classification and segmentation process of T1 weighted MR images. The system presented has an average accuracy of 94% for all the classifiers. Further, the segmentation process is validated as accurate through ground truth demarcations presented by a Neurologist. The average confidence interval for the tumor region extraction is 94.6%, which is a significant performance level. Possible future direction is to generalize the automation process for T2-weighted and Flair-weighted MR images of different planes, such as sagittal and coronal plane slices. Hence, the proposed system would provide an additional diagnostic support to healthcare centers with limited trained staff and resources.

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