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To cite this article: Madona B Sahaai and G R Jothilakshmi 2021 *J. Phys.: Conf. Ser.* **1921** 012080

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Hierarchical based tumor segmentation by detection using deep learning approach

Madona B Sahaai¹ and G R Jothilakshmi²

¹Research Scholar, ²Associate Professor, Vels Institute of Science Technology & Advanced Studies, Chennai, India

¹Principal Author: madona.se@velsuniv.ac.in

²Corresponding Author: jothi.se@velsuniv.ac.in

Abstract. Brain tumor is a cluster of abnormal cells that grows out of control in brain. Identifying brain tumor is challenging for doctors, since its impact will lead to danger for human life. Spotting of brain tumor using traditional methods is not accurate. Deep learning provides solution for detecting Brain Tumor in an efficient way. We have used MRI scan images. Since the image contains noise, image pre-processing work has been done to enhance the images. Deep learning methods for images works with Convolutional Neural Network (CNN). CNN has an advantage of extracting features by own. CNN has many hidden layers, where features are extracted and those features are learned for future prediction process. Single Shot Detector is used for detection of tumor region. SSD uses 8732 default bounding boxes mapped to the ground truth boxes for localisation process. Jaccard Overlap is used for match the default box with ground truth box. The detected whole tumor region is then used for segmenting the proper tumor region.

Index Terms: Segmentation, Detection, Deep Learning, Single Shot Detector, Brain tumor.

1. Related Works

In [1] paper, they have utilized different orientation of scanned MRI image. They present a solution for segmentation of Brain tumor using LinkNet network. LinkNet network is a Deep Neural Network. They identified that single network will not work for detecting tumor. So they used multiple networks for multiple angles' of images. They have used Sagittal, Coronal and Axial angles for images for detecting brain tumor. The overall accuracy for all angles of image is 0.73. In [2] paper, combining the extracted features with Convolutional Neural Network has given an improved accuracy. According to this paper, they have used central clustering as a clustering method for extracting features. These are then combined with AlexNet architecture (i.e) with 5 convolutional layer with pooling layer followed by Softmax layer to improve the classifying accuracy of brain tumor. They have also trained Radial Basis Function classifier and Decision Tree classifier for the comparing the results. [2] Paper compares the improved classifying percentage in the test dataset. With the combination of extracted features with CNN, 99.12% accuracy is achieved in test dataset. In [3] paper, they proposed segmentation of MRI images using Semantic Segmentation. It also explained about the improved regularization. The segmentation is achieved by Full Convolutional Network. The Paper [4] proposed a method of segmenting brain tumor using patch of images.



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These patch of images are used for training Convolutional Neural Network. They have used hybrid method by merging two and three path CNN. It has been identified that local and global features are used for predicting the results. Gliomas patients' dataset alone is used for segmenting the brain tumor. Probabilistic Neural Network has been used in Brain tumor detection [5]. Initially Histogram Equalisation is used for enhancing the Image Intensity values. Later they extracted Texture features like Contrast, Correlation, Energy and Homogeneity features using GLCM. These features are utilised into Probabilistic Neural Network for the Network to learn, which results in 90.96% accuracy. The paper [6] came up with an idea of multiple stages for segmenting tumor. They filtered out low intensity and medium intensity values from images, followed by Image Enhancement process using Morphological operations like Filling, Erosion followed by Segmentation process. They counted the number of segmented object using iteration process and segmented the extract tumor region.

2. Introduction

Brain tumor is growth of abnormal cells in brain. Many different types of brain tumor are non-cancerous (benign) and some are cancerous (Malignant). Primary brain tumor can be cured easily, but cancerous brain tumor spread to brain which will lead to dangerous for life. Diagnosing brain tumor is a tedious task by traditional method. It needs human intervention for the diagnosis. To identify brain tumor CT scan and MRI scan images are used. MRI scan usually provides more detailed information of soft tissues of brain than CT images. But when it comes to identifying the exact location of brain tumor with noises in images will lead to confusion among the doctors for predicting. Recent advancement in soft computing methods resolves the problem of detecting the tumor well. Deep learning for images plays a major role in detecting the brain tumor location effectively. Deep learning uses Convolutional Neural Network for deep digging into images for extracting features of its own and learning the features. Many architecture involved for extracting features, but VGG16 for Mobile Net V2 works well when extracting features, also works faster than Google Net and VGG19, R-CNN. Mobile Net V2 architecture will do well for classifying the different classes, but when it comes to localising the object, Single Shot Detector works good. Single Shot Object detector, detects multiple object at one time. It uses anchor boxes for identifying the object location. After detecting the object location, Mobile Net classifies the object. So, SSD-Mobile Net architecture will works in the hierarchy of Object detection followed Classification. Other Detector-Classifer like R-CNN uses Region Proposal Method for identifying the object. R-CNN works in the principle of two-step process. First step, it will create a region of interest. If the objects are likely to be present, it will classify the Object. R-CNN takes much time in detecting objects than SSD-Mobile Net. The Yolo method for detecting the object do same kind of process like SSD. But YOLO has pre-defined grid cells, (i.e) aspect ratio for identifying the object is fixed, whereas SSD makes 8732 prediction using 6 layers. In SSD, we can add up more Convolutional layers depending on Dataset.

3. Deep Learning

Deep Learning is a subset of Machine Learning, where Artificial Neural Network algorithms inspired by human brain. Similarly to how we learn from experience, Deep Learning algorithms would perform task repeatedly, each time tweaking it a little to improve the outcome. The word Deep Learning itself explains that it has Deep Layers that enabling learning. When Utilizing Deep Learning for images, Convolutional Neural Network will be helpful.

4. Convolutional Neural Network

Convolutional Neural Network is one among the Deep Learning approaches. It has been most widely used in Computer Vision applications. Convolutional Neural Networks works mostly with large number of Deep Layers. CNN is a Feed Forward Artificial Neural Network developed from Multi-layer perceptron [15]. In most common, CNN has 4 different layers [14]. They are 1. Input Layer, 2. Convolutional layers, 3. Pooling layers, 4. Fully Connected Layers. Input layer which takes image as input with 3-color channels (RGB). These channels are directly given into Convolutional Network. These channels will change its dimensions according to the architecture like AlexNet, VGG16, etc.

As the name depicts, convolutional layers, convolves random filter generated with the input image given. Convolutional layers extract features from the images by convolving with filters. In the initial layers, it will extract common features of images like edges, corners etc. When the convolutional layers goes deeper, it will extract image specific features like obtaining patterns from the image. Convolutional is computed by

$$C = \frac{W-F+2P}{S} + 1 \quad (1)$$

Where, W is the input size, F is the filter size, P is padding, S is Stride. Convolutional layers works on the principle of linear operation. Once after the convolutional process, there will be reduction in dimensionality of images without padding. Padding of image will retain the image size, but feature map will change. For AlexNet, there will be 5 convolutional layers, VGG16- has 13 convolutional layers with 3 dense layer. Improved accuracy depends on the depth of the layers. Activation layer has an activation function after every convolutional layer. It is precisely because of the features captured by activation CNN that the non-linear description are more prominent. Some of the activation function are ReLU, Sigmoid, and Tanh. Figure 1 shows how activation function will be used while training process.

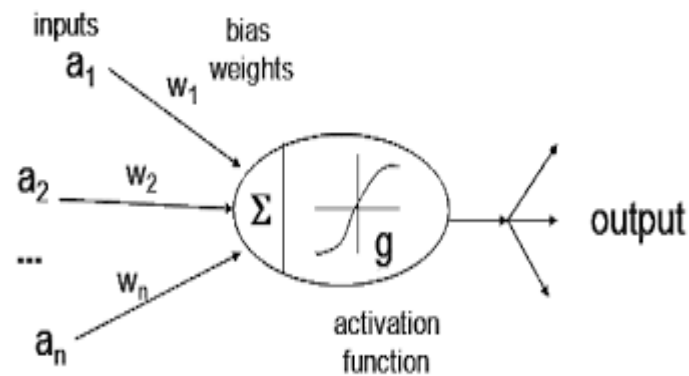


Figure 1. Activation function

In Sigmoid activation function while Back-Propagating, division operation occurs. For a deeper architecture, the gradient descent disappears also derivation of the function tends to zero. So after certain period of time, the training process will end up, resulting in over fitting. Whereas ReLU function only takes out the maximum value in the back-propagation. ReLU function can activate every pixel. ReLU is a Non-linear activation function and derivation in back propagation maintains piecewise linearity that makes the network to easily learn and optimise. Followed by convolutional layer, pooling layer is used for dimensionality reduction of feature map and network parameters. Pooling layer is translation invariant, because its computation takes neighbouring pixels into account. Pooling layer will reduce the redundant information present in the feature map which will also reduce the computation process. Pooling also acts as regularization technique to avoid over fitting. Pooling layer will down sample the image size which will forward the reduced image size into next convolutional process without redundancy. So using pooling layer, highest feature map values will be moved on to the next set of computation process using Maxpool with stride 2. From the output of the above layers, fully connected layers flatten them into single vector as neurons. Each neurons is then multiplied by a random weights initialised added with bias. Once the bias is added up, neuron has to be activated for the next layers. The process of activation relies on Relu, Signoid or Tanh. Relu has less computation with more activation power. Finally the Softmax activation function will gives the probabilities of each label. Calculation of the error probabilities using loss function will happen in final layer, which will back propagate the error to adjust the network parameter weights of all convolutional kernels to the find the minimal error in the consecutive iterations.

5. Proposed Work

In this paper, we applied SSD-MobileNetV2 for tumor detection followed by segmenting the tumor region. At first, we used tumor images directly for Segmentation. We initially used Contrast Limited Adaptive Histogram Equalisation (CLAHE) algorithm followed by other Image Enhancement techniques. Finally thresholding method is applied for Segmentation purpose. But we observed that, for each image that we used, there is a need for different threshold point and for drawing contours across it becomes a tedious process because many contours occur all over the image. Hence we identified that, detecting tumor region followed by segmentation process will be helpful. So this paper proposes a Hierarchical based tumor segmentation using Object detection method. The pipeline of the proposed work is shown in figure 2.

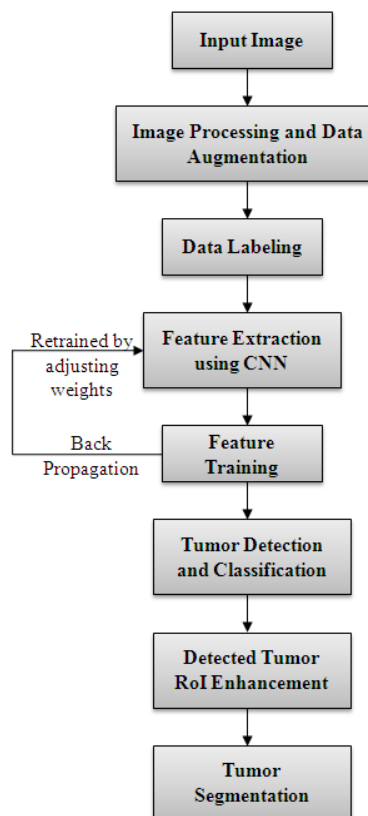


Figure 2. Proposed pipeline

Some of the input images that we used for training are shown in figure 3.

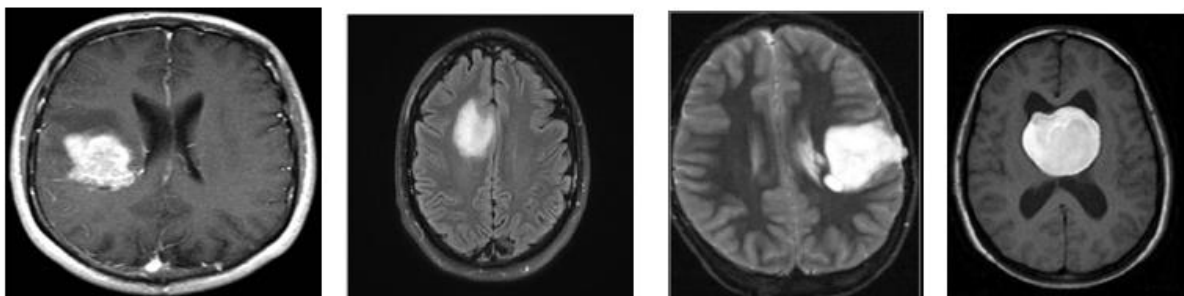


Figure 3. Input Images

Here we used VGG16 as a Base Network as a Feature Extractor for images. MobileNet V2 is used as an image classifier and Single Shot Detector as method for detecting the tumor region. MobileNet V2 is faster with improved accuracy across the entire latency spectrum. SSD will individually separate and distinct the space of bounding boxes into cluster of default boxes with different aspect ratio and scales feature map location. This method will not resample or rescale the pixel or features of bounding boxes. Thus by eliminating the bounding box proposal, detection speed is increased. Single Shot Detector works on the principle of Feed Forward Convolutional Network, which brings out fixed size collection of Bounding boxes and scores of each object present within the bounding box, followed by Non-Maxima Suppression to obtain final detection. Base layers will do only classification process. To enable the detection process, auxiliary structure is added to the network with the following key features. 1. Convolutional layers are added to the end of base network that will allow predictions of object detection at multiple scales. 2. For every feature layers of size $x*y$ with n channels, the standard element for possible detection is $3*3*n$ kernel that will result in score for the object category or shape offset relative to the bounding box co-ordinates. While training process, identifying the default boxes that corresponds to the ground truth detection. For every ground truth box associated with default box will be selected that has different aspect ratio and scales. Using Jaccard Overlap, ground truth box will get matched with the default boxes with threshold greater than 0.5. This simplifies the learning process. Weighted sum of Confidence loss and Localization loss will result in overall objective loss. It is calculated by,

$$L(a, s, l, t) = 1/N [L_{conf}(a, s) + \alpha L_{loc}(a, l, t)]$$

N is number of matched bounding box, Localisation loss is l , ground-truth is t . Our confidence loss is softmax loss over multiple classes confidence(c) and the weighted term α is set to 1 by cross validation.

The dataset we used is collected from Kaggle. It has 201 images with brain tumor, 95 images with Non-brain tumor. The dataset we had is very less. So Data Augmentation process is done for all images. We did basic image enhancement techniques like several noise removal and saved those images as augmented images. Image translation, rotation, brightness enhancement, Morphological operation are some of the data augmentation techniques that are done for generating more images. After Data Augmentation, Images are labelled. Labelling the tumor region will result in Region of Interest for the training or learning process. The process of labelling will be helpful in identifying the input patterns. Tensor flow framework is used for machines to learn. The ROI obtained from image labelling has to be converted into tensor flow record. Tensorflow record is nothing but a simple format for storing a sequence of binary record. Here the ROI is converted into sequence of binary record, not only for the machines to learn, but also for the optimized usage. Then we need to create label file. This file is intended to create because; mapping of labelling has to be done with respect to ROI while training of images. Hyper-parameter tuning is done while configuring the dataset record. ReLU activation function is used for better convergence. ReLU activation function depicts in the figure 4.

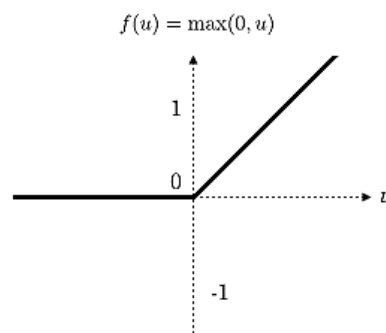


Figure 4. ReLU Activation

While training the loss obtained ranges between 0.5 to 1 in 4000+ steps. Tensor board graph for upto 20k steps has been shown in figure 5.

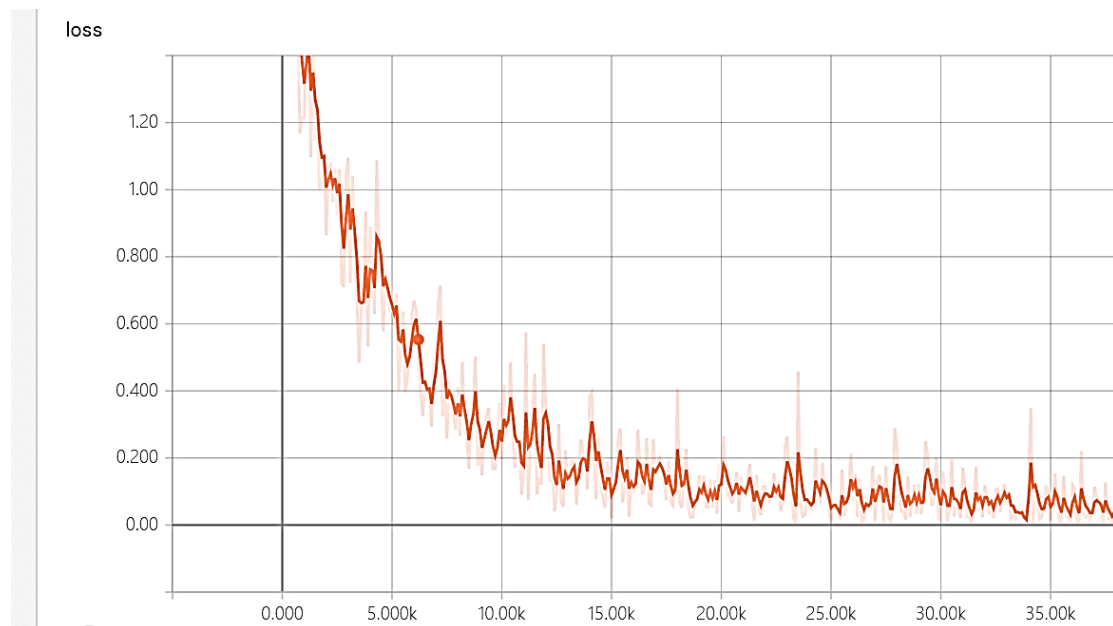


Figure 5. Overall Loss

The loss function calculated is viewed using Tensor board. The detection accuracy that we obtained is 0.9. Detection accuracy is good for 9 out of 10 images. The detected tumor region images are shown in figure 6.

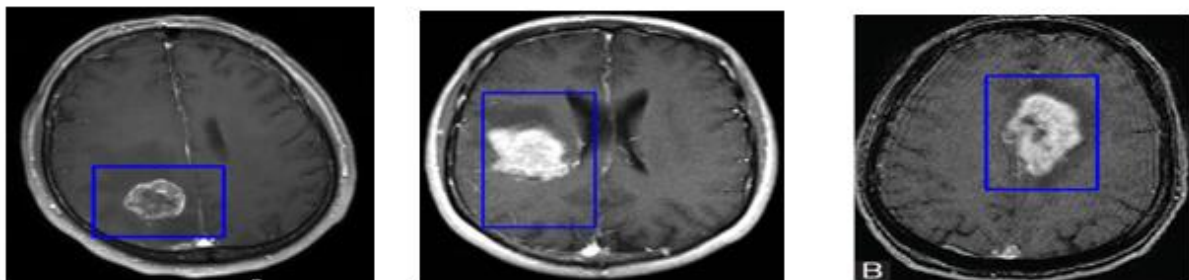


Figure 6. Detected Tumor

After the detection process, the obtained area of interest is used for Segmentation purpose. This hierarchical based Segmentation process gives maximum accuracy than other method of segmentation. The obtained area of interest is enhanced using CLAHE algorithm. CLAHE algorithm will do contrast enhancement process. Followed by CLAHE process, Gamma correction is done for brightness enhancement of images. The obtained image is then converted into grayscale image for Morphological dilation. Morphological dilation will enhance the brighter region brighter. The process is then followed by image thresholding technique for segmentation purpose. Here we used OTSU thresholding technique for segmentation. Brightness adjustment is calculated as:

$$\text{Gamma Correction} = \left[\left[\frac{\text{Original}}{255} \right]^{\frac{1}{\text{gamma}}} \right] \times 255 \quad (2)$$

6. Experimental Results

We used Google-Colab for our training process. By default Colab supports tensorflow-2.2 version. But the object detection we trained using tensorflow-1.5 version. Also we used Ngnix for viewing Tensor board training graph. When on detection, a score of 0.5 or greater value will be considered for performance evaluation. For every ground truth box, the algorithm generates an Intersection over Union with every detected box. A match is found only when ground-truth box and detection box is greater than or equal to 0.5. The IOU that we achieved is 0.85, (i.e) it is greater than 0.5. Using the IOU, loss will be calculated and back-propagation algorithm will adjust the weights according to the loss. With the data we achieved an overall accuracy of 90% for object detection. The detected tumor region is then used for segmentation purpose. This Hierarchical based segmentation provides better accuracy than other kind of segmentation. The Detected tumor region followed segmentation is shown in the figure 7.

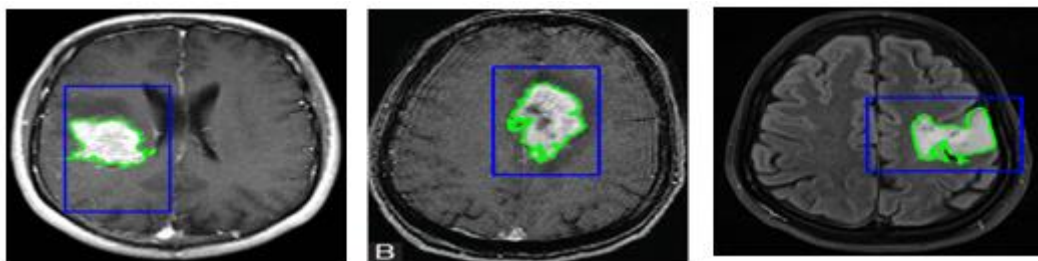


Figure 7. Segmented Tumor Region

7. Conclusion

Brain tumor detection using soft-computing methods are emerging these days. We proposed a method of segmenting the Tumor using hierarchical form. This Hierarchical method uses MobileNet architecture for extracting features of images and classification. These MobileNet models are light weights models that can also be deployed in Edge devices as needed. Followed by MobileNet, Single Shot detector is used for detecting the tumor. Single Shot Detector is used for localising the class. After localising the tumor, segmentation process happens within the detector are, which will increase the probability of segmenting properly. With the detection process, the proposed method achieves 90% overall accuracy and improved performance can be achieved with more number of training samples. Our future work will be classifying the types of brain tumor based on hierarchical based detection followed by segmentation and classification.

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