

Deep Convolution Network for Brain Tumor Detection and Segmentation from MRI Data

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1 Introduction

One of the fundamental problems of computer vision is image classification and segmentation where the task is to know the location of the object(s) contained in the image besides classifying the images according to their labels. This helps to get semantic understanding about the images and videos and they are related to many real world application such as tumor detection in medical images, face recognition, autonomous driving etc. In deep learning context the “object detection and segmentation” involves different sub-tasks such as localizing the objects in the image, find informative region, feature extraction, and classification [1].

An appropriate multiscale sliding window should be able to scan all the images and find the objects in the images that might appear in any positions and having different aspect ratios and sizes. After that, “feature extraction” will help to recognize different objects in the images for semantic and robust representation. Commonly used feature extraction methods are the scale-invariant feature transformation [2], histogram of oriented gradient (HOG) [3] etc. And then a classifier will help to distinguish the object from one class to other.

Brain tumor is considered as one of aggressive diseases, among both children and adults [4]. Every year, around 11,700 people are diagnosed with a brain tumor [5]. Brain tumors are classified as benign, malignant, pituitary tumor etc [6]. With a proper and timely diagnosis can improve the odds of success in brain tumor treatment. The best way to detect brain tumor is using the Magnetic Resonance Imaging (MRI). A huge amount of data is generated through the scans and examined usually by the radiologists. The manual examination can be error-prone due to the level of complexities involved in brain tumors and their properties. So, the application of automated classification techniques using machine learning and artificial intelligence has shown higher accuracy than manual classification. So, having a framework/model to classify and localize the brain tumor in MRI data will help the doctors all around the world [7].

2 Dataset

This study is planning to use an open data set called the BR35H::Brain Tumor Detection 2020 (BR35H) [8]. This dataset contains 255 negative and 255 positive MRIs of brain tumor.

3 Method

3.1 U-net for Image segmentation

U-net architecture is special type of deep learning framework for image segmentation where the convolution layers are arranged in such a way that results in image segmentation. U-net is designed for semantic segmentation. This architecture enable to have fast and precise segmentation of images [9]. This is an end-to-end segmentation technique which takes a raw image as input and outputs a defined segmentation map of the image. The u-shaped architecture with a symmetric convolution network has a down-sampling contraction and up-sampling expansion path. In the contraction path of U-net, it is often called encoder path and on the expansion path of it also called decoder path. Combining both the paths, this helps in image segmentation.

One of the advantages of U-net convolution network is that it does data augmentation as a part of the model training which is useful when the number of raw input is smaller or difficult to obtain. Moreover, U-net architecture allows touching/identifying objects in the same class that requires to be correctly separated. Here, is an example u-net architecture.

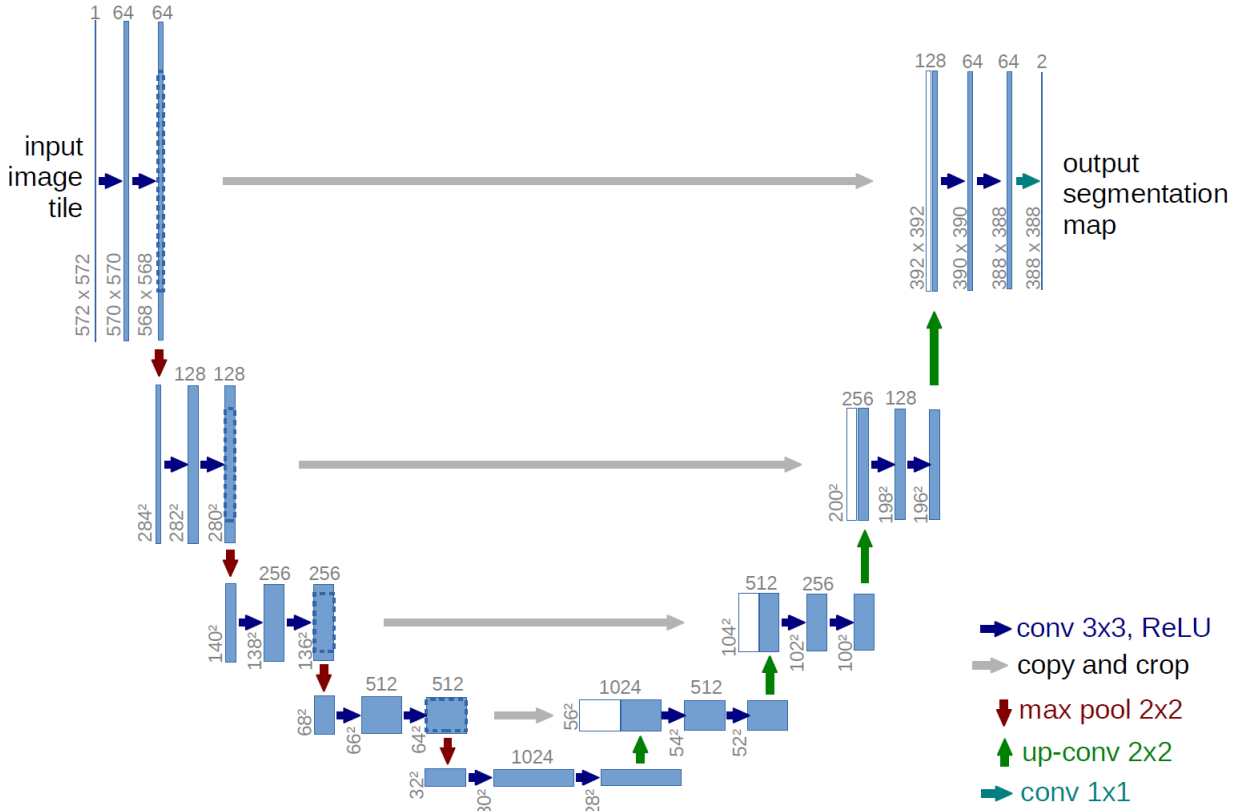


Figure 1: An example U-Net architecture [9]

In figure 1, an example U-net architecture is shown, where each blue box indicate to a multi-channel feature map. The top box, indicate the number of channels and the x-y size in the lower left edge of the box. And the white boxes represent copied feature maps. Finally, the arrows represent different operations [9].

This study will train the deep learning model to classify the tumors and with the help of U-net architecture and do the segmentation of the tumors. This study will also try to improve the existing deep learning architecture by experimenting with different learning function and optimize the function.

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