# Brain Tumor Detection and Segmentation Using Mask R-Cnn

[1]KAMBLE ATISH, [2]KHARE SURAJ, [3]MAHAMUNI SHREYAS, [4]MULLA HAIDARALI

Prof. Mrs. S. J. Chougule Department of Information Technology
Dr. J. J. Magdum College of Engineering, Jaysingpur

**ABSTRACT: One of the dreadful diseases that the world encounters moment is brain tumours. When abnormal cells form in the brain, it is called a brain tumor. There are a lot of variations in the sizes and positions of tumors, and hence this makes it really hard for a complete understanding of tumours. Radiologists can fluently diagnose the disease with the help of medical image techniques, but making this process automatic is obviously useful. Magnetic Resonance Imaging (MRI) is the most effective system for detecting brain tutors where, MRI images are trained and tested in order to descry the tumor. The automated system would be suitable to find and pinpoint the exact position of the tumor in an MRI image. Our study describes a method for segmenting abnormal brain tissues and determining whether the case has a tumor. This approach detects a unique area of the brain and forecasts the liability of a tumor developing there. Mask regional-based convolution neural network (Mask R-CNN) is a pre-trained deep neural network model that is used to distinguish objects from an image such as buses, animals, persons, trees, and other objects.**

**In comparison to numerous other analogous methods based on MLP, VGG-16 model, and U-net model, we discovered that Mask R-CNN method performs the best. The clarity of the MRI scans has a big impact on the delicacy. The proposed system was suitable to outperform similar systems on the same dataset, achieving a 74 percent crossroad over Union (IoU) score on the reference dataset, Brain MRI Images for Brain Tumor Detection. The demand for effective computer-aided brain tumour segmentation techniques has increased vastly in recent times. Still, accurate brain tumour segmentation is still a challenge because of its structural complexity such as variations in position, size, shape, overlapping tumor boundaries with normal brain tissues, etc. Existing automated approaches for brain tumour detection can be broadly categorized into handwrought features and deep learning (DL) based approaches. Qasem et al. [1] used a watershed segmentation algorithm along with the KNN for brain tumour classification and segmentation. This method performs well on the selected MRI images and is unable to accurately segment the tumour regions on challenging images containing tumors with multiple structural complexities.**

**INTRODUCTION:**

A brain tumor is a murderous-compliant million people around the globe and has a high mortality rate. Beforehand identification and segmentation of brain tumors help to increase the survival chances of the case and also save them from complex surgical processes. Moreover, the precise segmentation of brain tumors facilitates the surgeon for better clinical development and cure. The demand for effective computer-aided brain tumor segmentation ways has increased vastly in recent times. still, accurate brain tumour segmentation is still a challenge because of its structural complexity similar to variations in location, size, shape, and overlapping tumor boundaries with normal brain tissues, etc. Automated approaches for brain tumor discovery can be astronomically distributed into handwrought features and deep learning (DL) based approaches. Qasem et al used a watershed segmentation algorithm along with the KNN for brain tumor classification and segmentation. This system performs well on the selected MRI images and is unfit to accurately segment the tumor regions on challenging images containing tumors with multiple structural complications. In an encoder-decoder-based architecture was proposed to perform pixel-wise segmentation of tumor tissues from the normal brain cells. In FR- MRINet, a 33-layer deep model and an encoder with a completely connected decoder were proposed for tumor segmentation. This system provides better segmentation performance but at the expenditure of increased computational cost. In this letter, we propose an automated method to increase the robustness of brain tumor localization and segmentation by employing the Mask RCNN model.

**LITRATURE SURVEY:**

**Amin J., Sharif M., Gul N., Yasmin M., & Shad S. A. (2020).** This invention relates to improvement in Brain tumor classification based on DWT fusion of MRI sequences using convolution neural network. This method performs well on the selected MRI images and unable to accurately segment the tumour regions on challenging images containing tumors with multiple structural complexities.

**Charron. O, Lallement, A., Jarnet, D., Noblet, V., Clavier, J. B., & Meyer, P. (2018).** The present invention relates to Early identification and segmentation of brain tumour helps to increase the survival chances of the patient and also saves them from complex surgical processes. Automatic detection and segmentation of brain metastases on multimodal MR images with a deep convolution neural network.

**Rohini Basak Dept. of Information Technology, Jadavpur University, Kolkata700032,** The article gives all the clear clarification on the major key point on Mask regional-based convolution neural network (Mask R-CNN) is a pre-trained deep neural network model that is used to distinguish objects from an image. In comparison to many other similar methods based on MLP, VGG-16 model, and U-net model, we discovered that Mask RCNN method performs the best.

**Dubey YK, Mushrif MM (2016)** FCM clustering algorithms for segmentation of brain MR images. Adv Fuzzy System The backbone network is utilized to obtain relevant features from the input image. For implementation, we considered ResNet101 with a Feature Pyramid Network (FPN) backbone to extract more discriminating

and reliable features. The resulting feature map is further improved using the FPN that extracts the features with a better representation of the object at different scales for the region proposal network (RPN).

**METHODOLOGY:**

**Pre-processing**:

In the preprocessing step, we applied the position set system for bias field correction and median sludge to reduce the noise to get an enhanced image.

Tumor localization and segmentation using Mask RCNN:

For segmentation, our target is to automatically localize and segment the brain tumor from a complex background without taking any homemade intervention. We aim to prognosticate either tumor or non-tumor regions in the given MRI images using the Mask RCNN.

**Feature extraction:**

The backbone network is utilized to gain applicable features from the input image. For preparation, we considered ResNet101 with a Feature Pyramid Network (FPN) backbone to extract more discriminating and dependable features. The performing feature map is further improved using the FPN that extracts the features with a better representation of the object at different scales for the region proposal network (RPN).

**Region proposal network:**

The feature map computed in the former step is fed to the RPN network to induce ROIs. A 3×3 complication layer is used to overlook the image using a sliding window to generate applicable anchors that represent the bounding box with different sizes and are distributed over the entire image. There are about 20k anchors of distinct scales and sizes that correspond with each other to cover the image. Binary classification is performed to determine whether an anchor contains the object or background (FG/BG). The bounding box regression (BBR) generates bounding boxes according to set Intersection-over- Union (IoU) value. More specifically, if an anchor has IoU advanced than 0.7 with a ground-truth (GT) box, it is classified as a positive anchor (FG class), and else negative ROI classification and bounding box regression This network takes the proposed ROI and feature map as input (Fig. 1). Unlike the RPN, this network is deeper and classifies ROIs to a specific class similar as tumor/non-tumor, and further improves the size of the bounding box. The BBR aims to upgrade the position and size of the bounding box to exactly encapsulate the tumor region. Usually, the boundaries of ROI do not coincide with the granularity of the feature map as the feature map is down-sampled k times from the size of the original image. To resize the feature maps, the ROI Align layer is applied to extract fixed-length feature vectors for arbitrary-size candidate regions.

**Segmentation mask:**

The segmentation network takes positive ROI linked by the ROI classifier as input and returns a segmentation mask of 28×28 represented by floating numbers that contain further information over binary masks. The GT masks are scaled down to 28×28 to measure the loss with the prognosticated mask during the training stage. Still, during the inference, the predicted mask is scaled up to match the dimensions of the ROI bounding box and which provides the final output mask.

**Multi-task loss:**

The proposed model employs a multi-task loss L on each sampled ROI defined as:

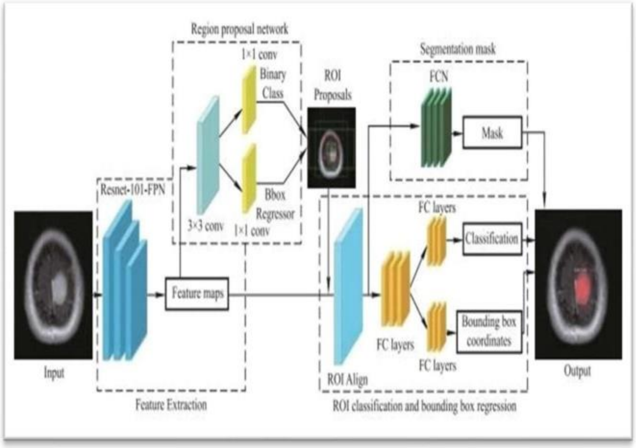


**Fig1. Region Proposal Network**

**RESULT:**

We have enforced the model using Keras and Tensor Flow libraries with ResNet-101, and FPN for feature extraction. We initialized the model using pre-trained weights attained from the COCO dataset and employed transfer literacy to fine-tune the model on MRI datasets for tumor segmentation. For trial experimentation, we used the 70-30 ratio that is aimlessly spitted into training (70%) and test (30%) sets.

**Dataset:**

The presented approach is estimated on two online available datasets, Brain Tumor Fig share (BTF) Dataset [6] and Brain Tumor Kaggle (BTK) Dataset [7] that are different in terms of structural complexity, accession angle, devices, noise, and bias field-effect, etc. We employed precision, recall, accuracy, dice score (DSC), and IoU to estimate the proposed method.

**Results and discussion:**

This section provides a discussion of the results attained after performing three different trails experiments. In our first experiment, we anatomized the performance of our technique on the BTF dataset and BTK dataset. Fig. 2 shows some of the high-scoring results of the segmented brain tumor attained by applying the Mask RCNN. The proposed method can accurately localize the brain tumor with an average precision of 0.952 on the BTF dataset and 0.948 on the BTK dataset from the healthy tissues despite spastic or blurry boundaries and vestiges in MR images similar to noise, bias field effect, and accession angle. Also, our method can precisely segment the brain tumor by overcoming the challenges of variations in position, shape, and size.

To further understand the performance of our method, we have drawn a boxplot for evaluation criteria on both datasets. The box plot represents the spread of results into four quartiles, a standard, and an outlier. Our method has achieved an average delicacy of 95.1% over the BTF dataset and 94.6% over the BTK dataset. Our method fails to accurately localize the tumor region in a few images, due to visual similarity with healthy tissues. In our next experiment, we have compared the performance of our method with other region-based segmentation methods, i.e., RCNN and Faster- RCNN using the BTF dataset, and results are reported.

**Hardware & Software used in proposedsystem:**

**Hardware:**

Hardware required for this system is as follows:
Processor: Intel i5, 7th generation.
Processor Speed: 2GHZ and above
RAM: 8GB
Hard Disk: 1TB and above

**Software:**

Operating System: Windows 10, 11.
Language: Python, ML, AI.
Database: Cloud
Browser: Chrome, Microsoft edge.

**CONCLUSION:**

In this letter, we have introduced a Mask RCNN model for the precise segmentation of brain tumor from the MRI scanned images. We showed the significance of Mask RCNN for brain tumor segmentation. The results illustrate that the proposed method precisely delineates the tumor region and serves as an effective automated tool for diagnostic purposes. We plan to extend our work by performing the classification of different classes of brain tumor we have compared the performance of our model with the existing latest approaches using the BTF dataset (Table 2). The proposed technique uses deep features that are more discriminating, reliable, and provide more effective representation of tumor regions over other methods such as [1], which employs the hand-crafted features and unable to better represent the tumor region due to structural complexities. Moreover, in some existing methods [2–4] segmentation is applied directly on the entire image, which results in misclassification due to complex background.

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