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# Detection of Brain Tumors with Help of Mask R-CNN

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**ABSTRACT**: brain tumor disease affecting millions of people around the world. If this disease is not diagnosed early, the survival rate of patients is very low. Therefore, the diagnosis of brain tumor must be fast and accurate. Mask-RCNN is a recently proposed state-of-the-art algorithm for object detection, object localization, and object sample segmentation of MRI images.

In this study, using a dataset consisting of 253 MR images with and without a tumor, and the location and size of the tumors were detected with MaskR-CNN, an accuracy rate of 88%-94% was obtained.

**KEYWORDS:**Convolutional Neural Networks, Brain Tumor, Mask-RCNN, Tumor Detection

## I. INTRODUCTION

A Brain Tumor is an abnormal growth of brain tissue that can be life-threatening if not diagnosed early and treated appropriately.Typically, Magnetic resonance imaging (MRI) and Computed Tomography (CT) scans are used by medical personnel to obtain detailed images of the brain for initial analysis in invasive procedures such as tissue biopsies. In addition, the use of computer-based image analysis in collaboration with medical knowledge can contribute significantly to aiding early diagnosis [1].

Several different types of algorithms have been studied for many years in the fields of image classification and segmentation, image processing for supervised and unsupervised feature extraction, and computer vision. Therefore, an increasing number of existing and new computer-based image classification and segmentation algorithms are being implemented and validated by many researchers in this field of study [2][3].

Misdiagnosis of a brain tumor can lead to a serious problem and reduce the patient's chances of survival. To overcome the disadvantages of manual diagnostics, there is an increased interest in designing automated image processing systems. [4]

## II. LITERATURE REVİEW

Mohammed et al. [5] compared the performance of K-Means Clustering and Fuzzy C-Mean Clustering techniques in three different data sets in tumor detection from MR images. They achieved an average accuracy of 92.27% with the K-Mean Clustering technique and 96.66% with the Fuzzy C-Mean Clustering technique.

Naghsh et al. [6] used the ROI method for tumor detection from MR brain images. The presented method consists of different image processing techniques such as morphological operations, low-pass filtering and thresholding. Tumor segmentation was performed with an average of 98.48% success from ten different data sets.

Sajjad et al. In their study, tumor region was selected by segmentation from MRIs for classification of brain tumors. Then, the classification process was carried out with the proposed Convolutional Neural Network (CNN) model. The success in classification is 94.58% [7].

In the study by İbrahim et al., MR images were classified using CNN. Data from the CIPR database were used as training data. The size of each image used in the developed model is 3x58. With the results obtained, the classification accuracy has been demonstrated as 96.33% [8].

Ghosh et al using the fuzzy k-means clustering algorithm with MRI images of patients, classified different tumor types in the brain and other brain-related areas with 89.2% accuracy.[9]

Bulut et al. proposed a model for brain tumor detection based on segmentation of MRI images. In experimental studies, brain tumors were detected with an accuracy of 87% using the Markov random field method.[10]

Mohammad et al. proposed a method they call CapsNet to classify brain tumors. With the proposed method, they aimed for a higher accuracy score with more data. For this purpose, they used 64 features obtained from a single convolution layer.

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They achieved an accuracy rate of 86.56% in the classification of brain tumors with the method.[11]

Ergin et al. proposed a method for detecting brain tumors on MR images, including deep learning and K mean segmentation. As a result of the study, they detected the brain tumor with an accuracy rate of 84.45% and a sensitivity of 95.04%.[12]

Swati et al. proposed transfer learning for multiclass classification of brain tumors. For this purpose, AlexNet used ESA models VGG16 and VGG19. In experimental studies, AlexNet achieved accuracy rates of 89.95%, 94.65% and 94.82% in VGG16 and VGG19 models, respectively.[13]

Firat et al. [14] suggested the use of 3 different machine learning methods for brain tumor detection: DVM, multi-layerperceptons (MLP) and logistic regression (LR). In experimental studies, they reached a 93% accuracy rate in detecting brain tumors.

Aslan M. MobilNetV2 deep learning model and K-Nearest Neighbors (KNN) algorithm were used to detect brain tumors with MRI images. In the study, full link layer values of the pre-trained MobileNetV2 model were used as features. The KNN classification algorithm was used to increase the classification performance of the obtained features. An accuracy score of 96.44% was achieved in the classifier.[15]

Ramteke et al. [16] used the nearest neighbor classifier as a classification algorithm for the statistical tissue properties of normal and malignant brain magnetic resonance imaging findings and achieved 80% classification accuracy. Similarly, Gadpayleand et al [17] classified normal and malignant brain MR images according to tissue properties and achieved 72.5% accuracy with a neural network classifier.

Abidin et al. [18] used the AdaBoost classification algorithm to detect metastases and glioblastoma tumors and achieved an accuracy of 0.71. In another study, Anaraki et al. [19] proposed a model of two combined rearrangements to classify brain tumor images based on convolutional neural networks (CNN) and genetic Algorithms, achieving 90.9% accuracy in classifying the three grades of glioma.

Khalil et al. They divided brain tumors into two classes as normal or abnormal. They extracted features on two different datasets by using three feature extraction techniques, namely GLCM, YIE and Histogram of Oriented Gradient (HOG). The feature vectors obtained with each technique were classified using the k-NN model.

In the experiment they performed on the first data set, they obtained 98.49%, 94.46% and 100% accuracy, respectively. With the second data set, they achieved success of 95.00%, 94.37% and 99.37%, respectively.[20]

Sultan et al. They proposed a deep learning model based on a convolutional neural network to classify different types of brain tumors using two publicly available datasets. While the first dataset includes meningiomas, gliomas and pituitary tumor types, the other dataset includes three grades of glioma (Grade II, Grade III and Grade IV brain tumor types.They stated that with the proposed network structure, they achieved 96.13% and 98.7% accuracy for the two data sets, respectively [21]

El-Dahshan et al. [22] using Discrete Wavelet Transform (DWT) to extract features, Principal Component Analysis (PCA) to reduce features introduced a method to classify 80 brain tumor normal and abnormal images, and then ANN and KNN to classify images with an overall accuracy of 97%. and 98% respectively.

Cheng et al. [23] proposed a method to improve brain tumor classification performance by magnifying the tumor region through image expansion and then subdividing it into subregions. They used three approaches to extract the features; The density histogram achieved the best accuracy of 91.28% using the Gray Level Co-occurrence Matrix (GLCM) and Bag of Words (BOW) and finally the ring form section in addition to tumor region magnification.

In this article, an experimental study was carried out on the localization of tumors using the MaskR-CNN algorithm from the CNN Family, one of the supervised machine learning algorithms in computer science for the detection of tumors on MR images. The findings show that MaskR-CNN performs well in determining the location of the tumors.

## III. THE PROPOSED METHOD

Mask R-CNN is an object recognition algorithm. It was released in 2018 by Kaiming He et al. It is the fourth member of the R-CNN family. Mask R-CNN is a branch of the Faster R-CNN architecture to predict the mask of anobject in addition to drawing a bounding box with the existing architecture of the Faster R-CNN algorithm.

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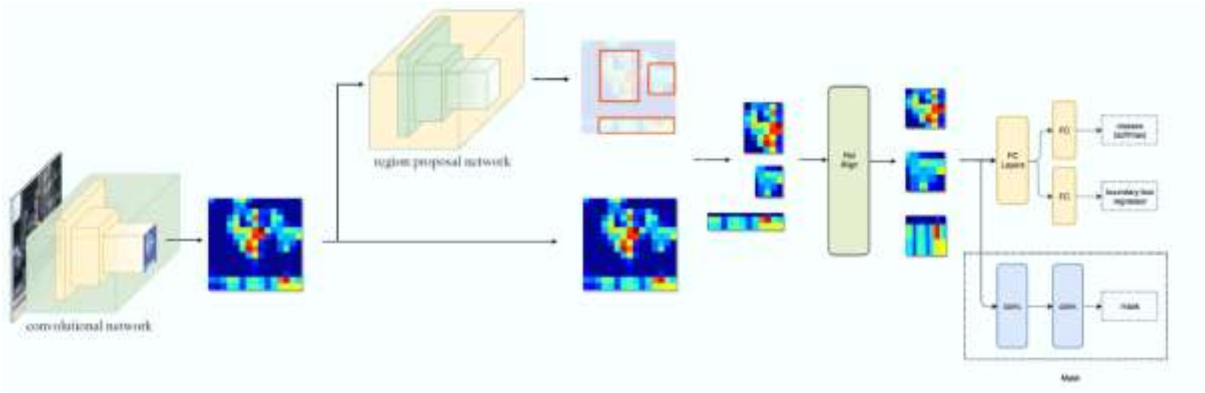


**Fig. 1. General Structure of Mask R-CNN**

It differs from classical object detection models such as Mask R-CNN, Faster R-CNN. Here, in addition to defining the class and the bounding box location, the pixels in the bounding box corresponding to that class are also defined. This pixel information may be necessary, for example, to detect the path in autonomous vehicles and the objects they want to pick up in robots.

**a. Region Proposal Network, RPN**

The feature map is obtained by passing the input image shown in Figure 1 through the convolution layers and this feature map is used as the input of the RPN. RPN, on the other hand, detects different sized identification frames at different locations, using the anchors of different sizes and aspect ratios, and detects areas that may be objects with the sliding window method. In this way, anchors that can contain objects are selected. If several anchors overlap too much, the one with the highest Intersection over Union (IoU) value is selected. This process is called non-max suppression. Thanks to this process, intersection regions (Region of Interest, RoI) are obtained

**b. ROI**

This network takes the proposed ROI and feature map as input (Figure 1). Unlike RPN, this network is deeper and categorizes ROIs according to a specific class such as tumor/non-tumor, further improving the size of the bounding box. BBR aims to improve the position and size of the bounding box to fully encapsulate the tumor site. Because the feature map is downsampled k times the size of the original image, usually the boundaries of the ROI do not coincide with the detail level of the feature map. To resize feature maps, the ROIAalign layer is applied to extract fixed-length feature vectors for candidate regions of arbitrary size.

**c. Mask R-CNNLoss Function**

it is calculated as follows:

$$LOSS = L_{\text{class}} + L_{reg} + L_{\text{mask}} \quad (1)$$

where $L_{\text{class}}$ is the loss function of each classification result, $L_{reg}$ is the loss function of the regression process used to determine the bounding box, showing the sum of the squares of the difference between the binary image and the label defined in each image, $L_{\text{mask}}$ corresponds to the loss function of the segmentation result.[24]

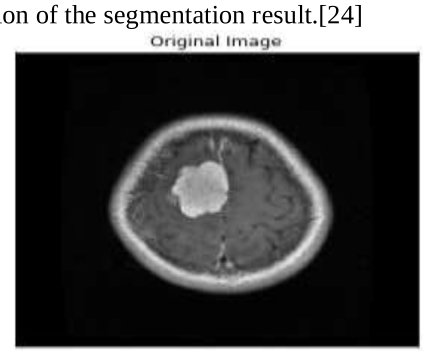


**Fig. 2a. Original image**

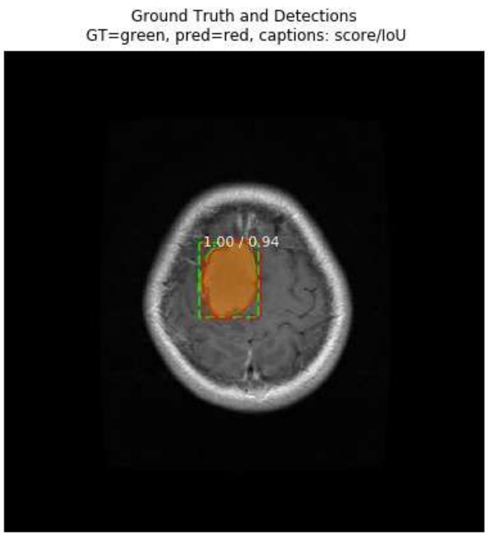


**Fig. 2b. Tumor detected by MaskR-cnn**

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**d. Dataset:**

The dataset is taken from the Kaggle site and consists of MR images of tumor patients, and it constitutes a total of 253 image datasets with 98 tumor less and 155 tumoral[25].

As the suggested method, the MaskR-CNNalgorithm is suitable for the aforementioned data set, and the algorithm tries to locate the tumor by scanning pixels on the images, and in case of correct detection of the tumor, the location of the tumor is determined in a red area.

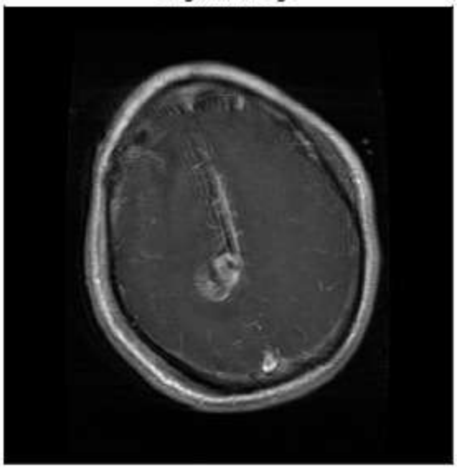


**Fig. 3a. Original image**

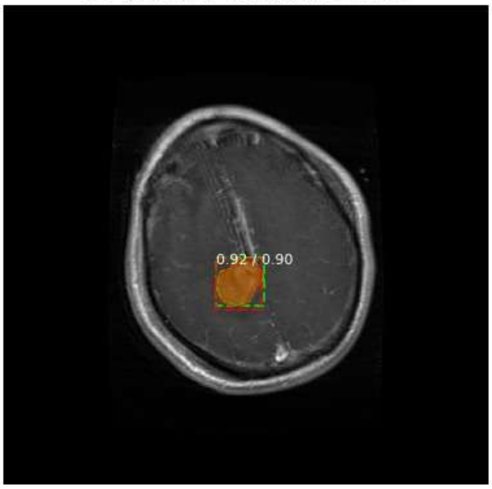


**Fig. 2b. Tumor detected by MaskR-cnn**

Before applying mask R-Cnn to MR images, a data preprocessing step was performed to accurately predict the location of the tumors on these images. In this way, the data was prepared for RPN. If the presence of the object is detected, it takes the accuracy value of 1 and switches to the regression layer in the visual RPN. In the regression layer, a bounding box is drawn around the object. The next step is to switch to the RoIAlign layer.In the RoIAlign layer, each object is additionally masked according to its spatial arrangement.

While using RESNET101 as the basic architecture, a pre-trained model with the COCO [26] dataset is used for training. In order for the MaskR-CNN algorithm to produce correct results, it is very important to determine the epoch number correctly. where the epoch number denotes the cumulative iteration number of the training process applied on the dataset.In the proposed method, the number of epochs is used as 15, and the accuracy rate is between 88% and 94%.

## IV. CONCLUSION

In this study, it is aimed to determine tumor location in tumor images using MaskR-CNN algorithm. For detection, a 3*3 kernel is created and moved across the image from left to right. where maskR-Cnn detects the location of the tumb by classifying according to the specified attributes. The accuracy rate obtained in this scope is between 88% and 94%. The algorithms are implemented with python 3 and run on a platform with a 2.59 GHz Intel i7 sixth generation CPU with 12 GB memory and an NVIDIA GeForce GTX 950m graphics card. The MR images used in this study are available free of charge at https://www.kaggle.com/datasets/navoneel/brain-mri-images-for-brain-tumor-detection for research purposes.

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