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Automated diagnosis of brain tumor classification and segmentation of magnetic resonance imaging images

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ABSTRACT

Brain tumors are one of the most prevalent disorders of the central nervous system and are dangerous. For patients to receive the best treatment, early diagnosis is crucial. For radiologists to correctly detect brain tumor images, an automated approach is required. The identification procedure can be time-consuming and prone to mistakes. In this work, the issue of fully automated brain tumor classification and segmentation of magnetic resonance imaging (MRI) including meningioma, glioma, pituitary, and no tumor is taken into consideration. In this study, convolutional neural network (CNN) and mask region-based convolutional neural network (R-CNN) are proposed for classification and segmentation problems respectively. This study employed 3,200 images as a training set and the system achieved an accuracy of 96% for classifying the tumors and 94% accuracy in segmentation of tumors.

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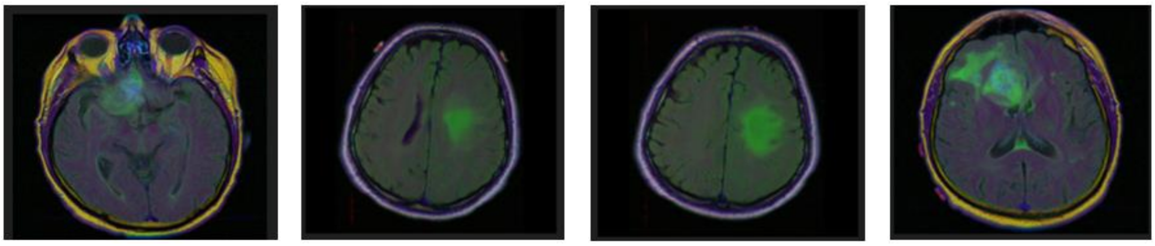
1. INTRODUCTION

A brain tumor is an abnormal growth emerging from the brain tissues, which might be fatal if not identified and properly treated at an early stage. In contrast to invasive treatments like tissue biopsies, medical workers often use magnetic resonance imaging (MRI) and computerized tomography (CT) scans to get comprehensive images of the brain for initial analysis. Additionally, the use of computer-based image evaluation in conjunction with medical expertise can greatly benefit early diagnosis. For supervised and unsupervised feature extractions, image classification, and segmentation have been investigated for a long time using a variety of techniques in image processing and computer vision. Convolutional neural network (CNN) [1] has recently emerged as the most widely used method for image classification and segmentation in a variety of research fields including diagnostic imaging, surveillance cameras, and factory automation to accomplish automation.

For supervised and unsupervised feature extractions, image classification and segmentation have been investigated for a long time using a variety of techniques in image processing and computer vision. CNN's capacity to extract more complex information from the input for such classification [2] task is its main draw. For instance, CNN designs like the Alex Krizhevsky network (AlexNet) are frequently used for medical image segmentation, while Google Net and image Net are widely utilized for computer vision and visual recognition. However, because of the computational expense and the lengthy training period linked to the system design, CNN applications have been constrained during the past ten years. But recently, because of improvements in current computer technology, particularly graphics processing unit (GPU), CNN's performance has significantly increased while processing times have been reduced [3].

Deep learning algorithms are now widely utilized in medical imaging to recognize regional anatomical features, locate organs and body components, and recognize various cell types [4]. According to literature, classifiers, neural networks, and machine learning algorithms can readily distinguish between normal and diseased classes of brain MRI. However, at this time, research on CNN's potential for tumor identification and segmentation is still in its early stages and is not very thorough. Figures 1(a) to 1(d) shows the types of tumors considered in this study.



(a) (b) (c) (d)

Figure 1. Types of tumors considered in this study; (a) pituitary tumor, (b) glioma tumor, (c) meningioma tumor, and (d) no tumor

2. RELATED WORK

Numerous studies have been conducted in the past on the subject of region of interest (ROI) segmentation and multi-view classification using CNN by a variety of authors. Tables 1 and 2 show the survey on healthcare applications based on classification and segmentation respectively. This work covers the knowledge and skills required to understand the research work covered in the portions of this section that came before it. The principles of image segmentation, along with its application and composition, are discussed here for the benefit of the reader. They classified the images from the contrast-enhanced magnetic resonance imaging (CE-MRI) dataset using a kernel learning algorithm, but they also employed CNN as a method to extract the features. They also contrasted the outcomes with several classifiers, including the support vector machine and radial base function. As the scientists noted, CNN is more effective because it yields more precise feature extraction findings, which are necessary for the classification step. In their proposal, the authors used two different approaches: first, a CNN model with a 28×28-pixel input layer, accompanied by convolution, batch normalization, rectified linear unit (ReLU), Maxpooling, and one convolution layer; and second, keyword extraction and synonym substitution (KE-CNN) to categorize the images into 3 groups. The two components of KE-CNN are CNN, which is used for feature extraction, and the output, a feature vector utilized as an input for Kernel extreme learning machine (KELM), which takes the role of the linked layer and performs classification. Radial basis function (RBF) serves as a kernel function in KELM. Despite the authors revised solution model, 93.68 % accuracy was still attained [5]–[7].

The author's approach used two separate techniques: first, a CNN model used a pre-trained deep classification algorithm as the extracting features. They built their idea on block-wise fine-tuning using transfer learning, which works with tiny datasets and produces workable results. Even though their proposal included a pre-processing step, the average multimedia tools as well as applications accuracy was 94.82 % [8]. The pre-processing method used was meant to reduce memory needs and accelerate the process by normalizing the CE-MRI datasets using a minimum-maximum strategy and then resizing it from 512×512 to 224×224. Following that, they replicated the scaled images 3 times, based on the visual geometry group 19 (VGG19's) i/p size. Due to the short dataset, they initialized the weights from the pre-trained model during training to prevent overfitting. Additionally, it was divided the 19 layers into 6 blocks because processing and fine-tuning each of the 19 layers would take a long time. Additionally, they achieved an overall accuracy of 89.52%. The first to publish the image database utilized in this research identified tumor types utilizing enhanced tumor ROI, image dilatation, and ring-form partition. They retrieved features with an accuracy of 91.28 % using the intensity histogram. Further articles that made use of the same data are addressed. There, we cover several network types, including trained ones, capsule networks, and additional convolutional network designs, and combine them with neural network models for extracting features and classifications for the output [9].

They utilized the clever edge detection model compounded with adaptive thresholding for extracting the ROI based on edge detection methodologies. 102 images were included in the dataset. Images were initially pre-processed, after which a second set of CNN architecture was used: the first set was used for clever edge detection, while the second set was used for adaptive thresholding. The Harris technique is used to extract character traits from its segmented image, which is then indicated by a level number. Then, 2 neural networks are used, the first to determine if the brain is healthy or has a tumor, and the second to determine the type of tumor. When comparing these two models and depicting the findings, the clever edge detection technique produced more accurate results [10]–[12].

The proposed segmentation method resembled a histogram. Regarding the segmentation of brain tumors as a three-class classification challenge (tumor comprising necrosis and tumor, edema, and normal tissue) including the two modalities fluid-attenuated inversion recovery (FLAIR) and T1. A region-based contour-based model using FLAIR modality was used to find the aberrant areas. By using the k-means approach and the contrast adjustment T1 modality, the edema and tumor tissues were discriminated in the aberrant areas, achieving a dice ratio and sensitivities of 73.6% and 90.3%, respectively [13]. They provided a system that incorporated two feature-extraction techniques before applying a binary classifier to determine the categorization of the i/p. This paper extracted features using a two-dimensional (2D) wavelet approach by making several copies of the input and applying various functions to each to obtain various degrees of complexity with an estimate in each. They also applied the previously stated Gabor filter method. Then, for the classification, they used back-propagation neural networks with three neurons in the output layer, 90 neurons in a single hidden intermediate layer, and 270 neurons in the input layer [14].

The fuzzy c-means clustering approach, followed by conventional classifications and CNN, is a technique we introduced in this study to extract brain tumors from 2D MRI. Real-time data with various tumor sizes, locations, forms, and image intensities was used for the experimental investigation. We used six conventional classifiers in the scikit-learn-implemented traditional classifier part. Then, because it performs better than conventional ones, we moved on to CNN, which is constructed using Keras and TensorFlow. In this research, CNN achieved an impressive accuracy rate of 97.87 % [15]. Proposed the paper brain tumor segmentation using JeisloNet - Unet architecture. In this study, an Unet architecture called JeisloNet was created for automatically segmenting problematic tissues, such as brain tumors, in MR scan data. The cancer imaging archives provided MR scans of the brain, which were pre-processed and divided into train and test sets in an 80:20 ratio. The model design, which is based on the Unet, consists of an expansion or up-sampling path and a contraction or down-sampling or encoding path. Input blocks of 256×256. Four steps make up the contracting route, each of which comprises two convolutional layers followed by a ReLU and a down-sampling procedure. The experiment's findings demonstrated that Unet architecture, JeisloNet, performed well, with dice coefficient index (DSC) values of 0.9931, mean intersection over union (IoU) values of 0.9321, global accuracy values of 0.9928, and error rate values of 0.0072 [16]–[18].

In this paper, they provide a CNN training technique that uses learned linear mapping functions and non-negative integers to estimate weights and activations. The fundamental insight of our task is that the scalability and translation considerations for weights can be trained along with other characteristics, whereas activations are typically normalized by batch normalization and ReLU, allowing for accurate approximation of activations using a single function across all layers that is pre-calculated based on the common half-waves gaussian distribution. The model quantized by the trained affine mapping technique utilizing 2-bit weight and activations obtain an average dice value within 0.01 compared to the full-precision model, according to evaluation findings from the BraTS 2018 competition [19].

This research develops a segmentation approach for brain tumors. Images are segmented using region-based and edge-based methods for this purpose. This work makes use of the brain tumor segment 2020 (BraTS2020) dataset. A comparison of the edge-based and region-based approaches to image segmentation utilizing the U-Net along with ResNet50 encoder architecture is carried out. The suggested approach includes segmentation, edge and area identification, and data preparation. The provided MRI image is first pre-processed, then brain boundary or region boundary detection is done, and finally, segmentation is done to display the tumor area. Its dice loss score was 0.008768, IoU score was 0.7542, f1 score was 0.9870, accuracy was 0.9935, precision was 0.9852, the recall was 0.9888, and specificity was 0.9951 [20]. In this paper, to further the field of brain tumor segmentation research, this work suggests the 2D image segmentation technique BU-Net. The basic U-Net design makes use of wide context (WC), residual extended skip (RES), and a bespoke loss function. The high-grade glioma data from the BraTS2017 and the testing data for the BraTS 2017 and 2018 datasets were used to evaluate the proposed BU-Net. Tumor core (TC), whole tumor (WT), and enhancing core (EC) were the three main labels to segment (EC). First, the 210-case BraTS 2017 high-grade gliomas (HGG) dataset was used to assess the proposed model. 80% of these instances were utilized for training, while the remaining 20% were used for testing. The BraTS challenge establishes the training and testing instances [21].

In this paper, the rich information about brain tumor architecture provided by MRI scans makes it a crucial tool for accurate treatment. A brain tumor segmentation and identification method is presented to address this issue, and tests are conducted. For each patient in this data, four separate MRI modalities T1, T2, T1Gd, and FLAIR are included. As a result, a segmentation image and the ground truth for tumor segmentation, or class label, are supplied. The tumor location was localized using the U-Net deep learning model; the contracting section of U-Net effectively captures the information from the compressed feature extraction and expansion route localization. Asymmetric parameter tuning of the contracting and expanding route layers was used to obtain great accuracy [22], [23]. In this paper, a mixture of the new architectures SegNet and UNet is the planned USeg-Net and SegU-Net. By comparing the suggested hybrid architecture with the widely used CNN models for segmentation, U-Net, SegNet3, SegNet5, and, it is possible to examine the segmentation capabilities in terms of accuracy. The enhancing tumor, necrotic and non-enhancing tumor, peritumoral edoema, and anything else are each represented by the colors green, red, yellow, and grey, respectively. Each model passes 172,800 neurons through the various hidden layers after accepting them as input in the input layers. In the output layer, these neurons are divided into four types. Five metrics are taken into account to assess how effectively the model executes segmentation tasks: global correctness, mean correctness, mean intersection over union, weighting IoU, and mean BF-scores [24]. The mean accuracy for the U-SegNet, Seg-Unet, and Res-SegNet, was 91.6%, 93.1%, and 93.3%, respectively.

As per the paper, they suggest an automated technique using the mask region-based convolutional neural network (RCNN) framework to improve the stability of brain tumor detection and segmentation. Tumor segmentation and localization with pixel-to-pixel accuracy utilizing the region proposal network (RPN) [25]. To demonstrate the effectiveness of our strategy, a thorough quantitative and qualitative analysis of the recently developed methodologies was conducted on two internet datasets. The suggested method is resilient to MRI aberrations such as noise, bias field effects, and varied acquisition angles as well as differences in tumor size, size, location, and overlap with normal brain tissues. Researchers used learning to perfect the model using MRI data for segmentation after initializing it with pre-trained weights of the common objects in context (COCO) data. For the experiment, they employed a 70:30 split, with training sets making up 70% and test sets making up 30%. Table 1 shows the survey on healthcare applications based on classification. Table 2 shows the survey on healthcare applications based on segmentation.

Table 1. Survey on healthcare applications based on classification

Sr no.	Paper	Year	Author	Dataset	Accuracy (%)
1	[3]	2018	Pashaei *et al.*	CE-MRI Dataset	93.68
2	[4]	2019	Swati *et al.*	CE-MRI Dataset	94.82
3	[5]	2015	Cheng *et al.*	CE-MRI Dataset	91.28
4	[6]	2017	Badran *et al.*	Kaggle Dataset	90
5	[7]	2016	Song *et al.*	BRATS 2012 and 2015	98
6	[8]	2018	Ismael and Qader	Figshare Website	91.9
7	[9]	2020	Hossain *et al.*	BRATS Dataset	97.87

Table 2. Survey on healthcare applications based on segmentation

Sr no.	Paper	Year	Author	Dataset	Accuracy (%)
1	[10]	2021	Zhang *et al.*	Cancer Images Archives (TCIA)	99.2
2	[11]	2022	Wang and Lin	BraTS 2018	88
4	[12]	2022	Kapoor and Agarwal	BraTS 2017 and 2018	90
5	[13]	2021	Rehman *et al.*	BraTS 2018	98
6	[14]	2020	Arora *et al.*	BraTS Dataset	93.3
7	[15]	2021	Daimary *et al.*	Brain Tumor Figshare (BTF)	95.1

3. METHOD

3.1. Data preparation

In this study, a T1-weighted brain tumor dataset comprising 4,000 MRI images is presented. The dataset, sourced from Kaggle, encompasses meningioma, glioma, pituitary, and no tumor cases in axial planes. The dataset is initially partitioned into training and testing sets.

3.2. Proposed system architecture

3.2.1. Proposed architecture for classification

The Figure 2 represents the block diagram of classification. It consists of two phases i.e., the training phase and the testing phase. Before the training and testing phase, the dataset will be split into 80:20 ratios for the training and testing part.

3.3. Training phase

In the training phase, the first step is to train the model with the image dataset. After the images are given to the model they are labelled based on the requirement. In our project classification of the brain tumor

MRI images are of four classes so the labels are as follows pituitary tumor in Figure 1(a), glioma tumor in Figure 1(b), meningioma tumor in Figure 1(c), and no tumor in Figure 1(d). Then the images undergo the pre-processing step where resize of the images takes place. With feature extraction, which is a sort of dimensionality reduction, a sizable portion of the image pixels are properly represented allowing for the effective capture of the image's relevant details. The output of the feature extraction which consists of feature maps is given as an input to the CNN. In CNN, the images undergo four steps i.e., convo 2D+ReLU, Maxpooling, flatten layer, and dense layer which will help to give the prediction model. After every cycle, the model calculates the loss function which is nothing but the error rate.

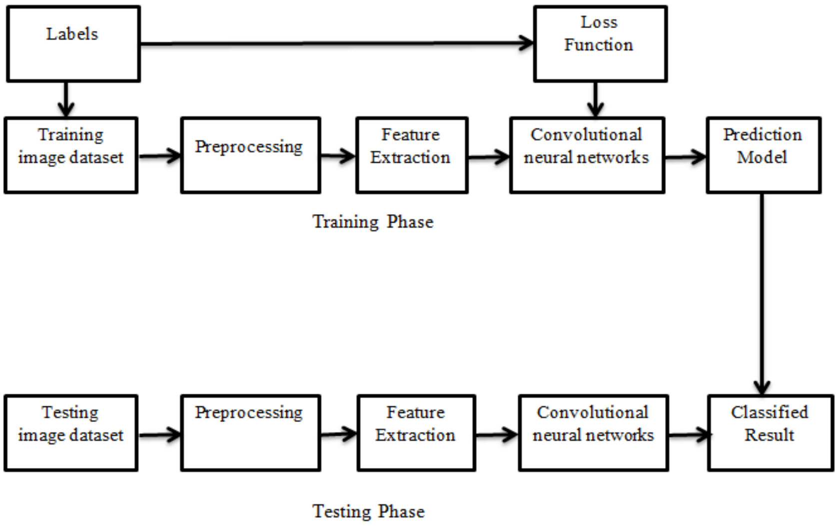


Figure 2. Block diagram of classification

3.4. Testing phase

In the testing phase, the images are given as input to the pre-processing step where the same procedure as training takes place. After the pre-processing the extraction of feature maps is given as the input to the convolution neural networks and then the results are compared with the prediction model. Finally, the classified results are obtained in comparison with the prediction model.

3.5. Architecture of convolutional neural network

CNN are a family of artificial neural networks used most frequently in deep learning to interpret visual data as depicted in Figure 3. CNNs are created by modifying multilayer perceptrons. Each neuron in one fully -connected layer is linked to every neuron in the layer above it and is known as multilayer perceptrons. An advanced kind of artificial neural network known as a CNN substitutes the mathematical operation. There are four layers in the CNN model they are as follows convo 2D+ReLU, Maxpooling, flatten layer, and dense layer. Figure 3 shows the CNN architecture.

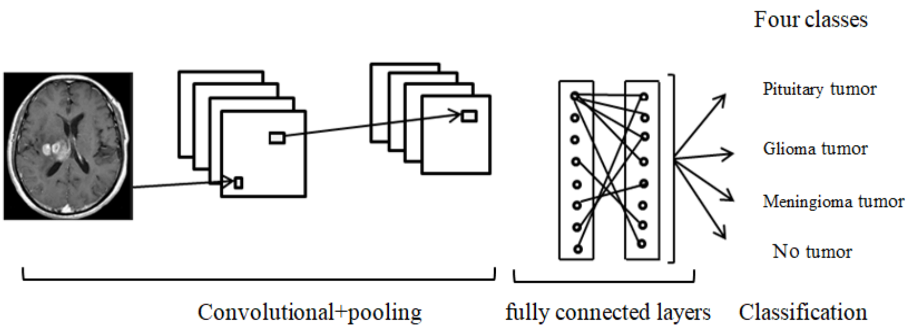


Figure 3. CNN architecture

3.5.1. Convo 2D+rectified linear unit

Because characteristics of the image are extracted within this layer, this layer is known as the feature extractor layer. Before performing the convolution operation previously, a small portion of the image is linked to the Convo layer to compute the linear combination between the filter and receptive field. One integer representing the output volume is the operation's output. The filter is then moved by a Stride across the following receptive field of the identical input image, and the process is repeated. The process will continue until the entire image is processed. The subsequent layer's input will be the output. Additionally, the convo layer has ReLU activation to set all negative values to zero.

3.5.2. Max pooling

After convolution, the spatial size of the input image is compressed using a pooling layer. Between two convolution layers, it is employed. It would be computationally costly and undesirable if fully-connected were applied after the Convo layer without using pooling or maximum pooling. Therefore, maximum pooling is the sole method for reducing the spatial size of the input image. In Figure 4, max pooling is used in a single scale slice with a stride of 2. As you can see, the input's four dimensions are reduced to two.

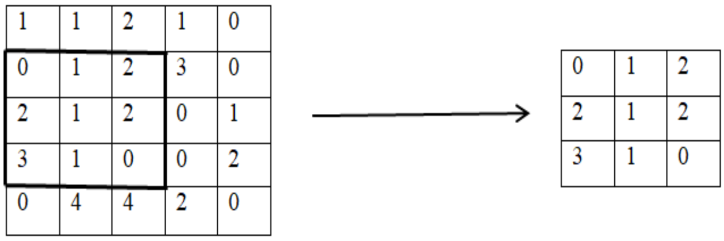


Figure 4. Max pooling

3.5.3. Flatten layer

This layer depicted in Figure 5 performs the conversion of 2D vector features to 1D vector features. The transformation is essential for simplifying the representation of features from a two-dimensional to one-dimensional format. This process aids in more efficient data handling and analysis.

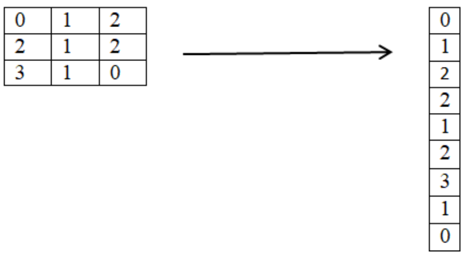


Figure 5. Flatten layer

3.5.4. Dense layer

In the basic layer of neurons, referred to as the dense layer, each neuron receives information from every cell in the layer beneath it. This layer utilizes the results obtained from the preceding convolutional layers to categorize images effectively. The dense layer's comprehensive connectivity allows it to capture complex patterns and features for accurate image classification.

3.6. Proposed architecture for tumor segmentation

3.6.1. Preprocessing

In the pre-processing step, noise is reduced using a median filter, contributing to improved image quality. Simultaneously, resizing is implemented to optimize the images for further analysis or tasks. These steps collectively enhance the data quality and prepare the images for more effective processing.

3.6.2. Tumor localization and segmentation using mask region-based convolutional neural network

Segmentation is employed to autonomously identify and isolate brain tumors from a complex environment without human intervention. The mask RCNN as shown in Figure 6 is utilized for this purpose, aiming to identify tumor and non-tumor areas within the provided MRI images. The goal is to achieve precise delineation and classification of tumor regions through automated processes.

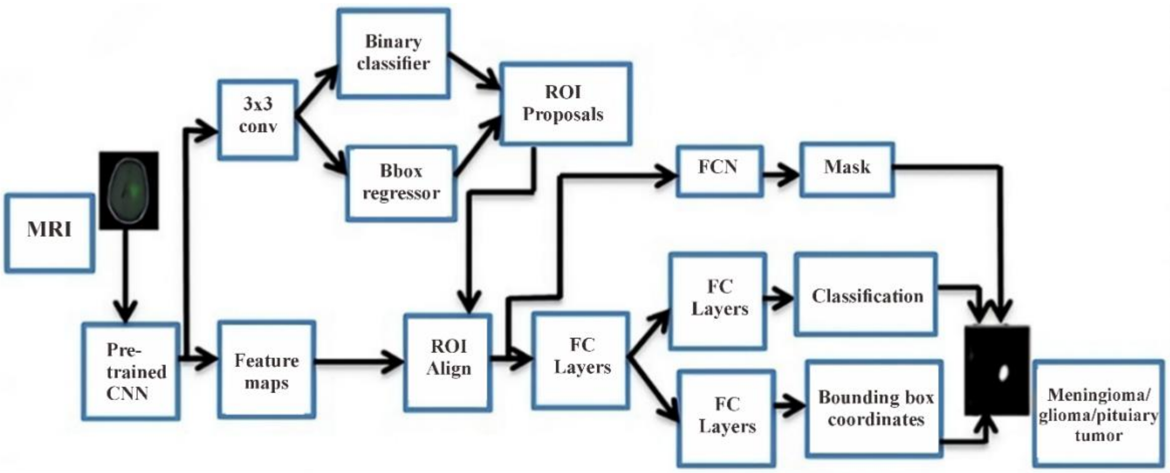


Figure 6. Proposed framework architecture

3.6.3. Feature extraction

The pre-defined CNN is used to obtain the relevant features from the input image. For extracting more discriminating and reliable features ResNet 101 is considered in the implementation. The final feature map from the intermediate layer with a more accurate representation of the image at various sizes is given as input to the RPN.

3.6.4. Region proposal network

The RPN network receives the feature map obtained in the preceding step and generates ROIs. Utilizing a sliding window to scan the image, a 3×3 convolutional layer creates essential anchors that symbolize the bounding box in various widths and are dispersed over the whole image. The image is covered by around 20k anchors of various sizes and scales that correlate with one another. The RPN network has two outputs i.e. binary classification and bounding box regression. Binary classification is used to identify whether an anchor contains the object or not. Bounding box regression builds bounding boxes according to the IoU value. A positive anchor is defined as one that has an IoU value of more than 0.7 and with the ground-truth box as opposed to a negative anchor.

3.6.5. Region of interest pooling

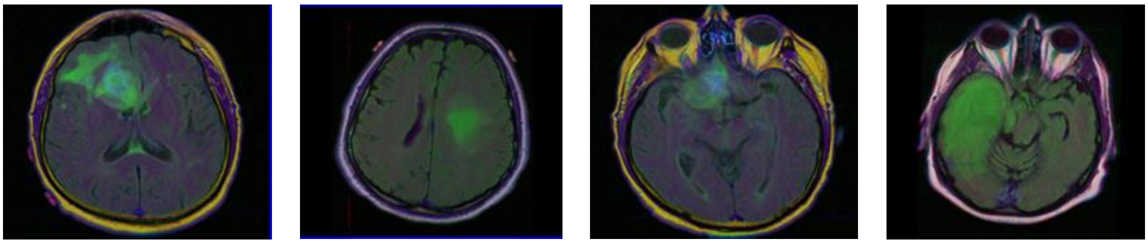
The designed ROI as well as the feature map are inputs to this network Figure 2. The ROI pooling network is deeper than the RPN, classifies regions of interest according to a certain category, like tumor or non-tumor, and enhances the bounding box size. The goal of the bounding box regression is to precisely enclose the tumor region by adjusting the size and placement of the bounding box. The feature map is down-sampled nearest k from the dimension of the original image; the bounds of the ROI typically do not correspond with the resolution of the feature map. The ROI align layer is used to extract fixed-length feature maps for arbitrarily defined candidate regions, which is then used to scale the feature maps.

3.6.6. Segmentation mask

A segmentation mask is represented by floating integers, which carry more information than binary masks and are produced by the segmentation network from the positive ROI recognized by the ROI classifier. To evaluate the loss with the expected mask during the training stage, the ground truth masks are reduced. However, the predicted mask is scaled up during inference to match the parameters of the ROI bounding box, producing the final output mask.

4. RESULTS AND DISCUSSION

The results of the suggested classification are displayed in Figure 7 as classification results; Figure 7(a) no tumor, Figure 7(b) glioma tumor, Figure 7(c) pituitary tumor, and Figure 7(d) meningioma tumor and segmentation in Figures 8 to 10 approach for brain tumors are presented in this section. Many images were used to validate the suggested technique, which was developed using the tensorflow and keras packages in Python. The outcomes are examined twice: first, in terms of the classification data's accuracy, and subsequently, in terms of the extracted tumor mask's accuracy. The aim of optimizing the proposed methodology to be able to categorize the tumors with the maximum performance for a particular kind of imaging modality, namely T1 MRI images, was employed in the work presented. Additionally, only axial plane slices are used in this experiment since these have a greater resolution and less noise than coronal and sagittal plane planes. The radiologists might continue with further examination utilizing both coronal and sagittal plane slices once the tumor is initially found in axial plane slices.



(a) (b) (c) (d)

Figure 7. Classification results; (a) no tumor, (b) glioma tumor, (c) pituitary tumor, and (d) meningioma tumor

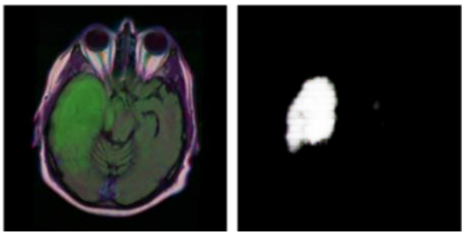


Figure 8. The segmentation of meningioma tumor

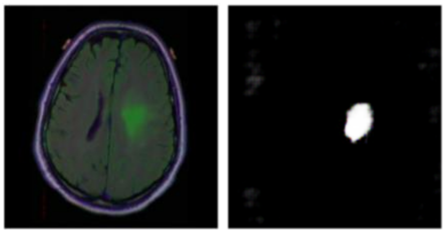


Figure 9. The segmentation of glioma tumor

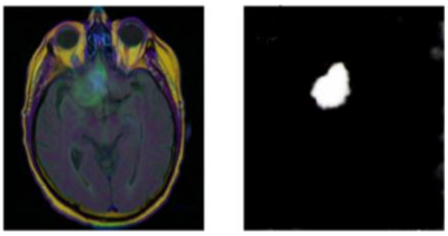


Figure 10. Figure showing the segmentation of pituitary tumor

5. CONCLUSION

This work focuses on the classification and segmentation of brain tumors from T1-weighted MRI images using an innovative CNN-based technique. The method showcased achieves an impressive overall classifier accuracy average of 96%. Additionally, segmentation is performed using mask R-CNN, yielding a segmentation accuracy of 94%. The potential future extension of the automated approach to include flair and T2-weighted MRI images, as well as slices from other planes like coronal and sagittal, could provide valuable diagnostic support for medical facilities facing shortages of skilled personnel and resources. This suggests the method's adaptability and potential impact on improving healthcare outcomes in resource-constrained settings.

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