RESEARCH ARTICLE OPEN ACCESS

Segmentation of Brain Tumor

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Abstract:

One of the most common and harmful illnesses of the central nervous system is brain tumors. Early diagnosis is essential for patients to obtain the best care. Radiologists need an automated method to accurately identify brain tumor images. The identification process can be lengthy and error-prone. The subject of completely automated brain tumor segmentation of Magnetic Resonance Imaging (MRI) is taken into account in this study, encompassing meningioma, glioma, pituitary, and no tumor. For segmentation issues mask region-based convolutional neural network (R-CNN) is proposed in this paper. In this study, 3,200 images were used as a training set, and the system segmented tumors with an accuracy of 94%.

Keywords — **Magnetic Resonance Imaging (MRI), Convolutional Neural Network, Segmentation, Brain tumor.**

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I. INTRODUCTION

Brain tumor is an abnormal growth emerging from the brain tissues that might be fatal if not identified and treated correctly at an early stage. Early detection and segmentation [1] of brain tumors improve the patient's chances of survival and spare them from difficult surgical procedures. Additionally, the accurate segmentation of brain tumors aids the surgeon in more effective clinical treatment and recovery. In recent years, there has been a noticeable growth in the need for efficient computer-aided brain tumor segmentation approaches. However, due to its anatomical complexity, which includes fluctuations in location, size, form, and overlap of tumor borders with healthy brain tissues, precise brain tumor segmentation is still difficult.

Tumors those develop in the pituitary gland are known as pituitary tumors. According to how they operate biologically, pituitary adenomas are often categorised into three groups: benign tumors, invasive tumors, and carcinomas. The majority of tumors are benign, just 35 % of them are invasive, and only about 0.1 to 0.2% of them are carcinomas. But since the pituitary gland is situated at the bottom of skull, many of them push on the optic nerves, impairing eyesight. Pituitary tumors are often removed in this manner. Transsphenoidal refers to the surgical procedure being performed through the sphenoid sinus, a hollowed area of the skull located below the brain and below the nasal passages.

A glioma is a particular kind of tumor [2] that develops from glial cells that are in brain or spine. About 30% of all the brain tumors and tumors of the central nervous system are gliomas, and 80% of all the malignant brain tumors are gliomas. The location of the central nervous system that is affected determines the symptoms of gliomas. Due to elevated intracranial pressure, a brain glioma can result in migraines, nausea, diarrhoea problems. Visual loss may be brought on by an optic nerve tumor. Gliomas of the spinal cord can result in discomfort, numbness, or paralysis in the limbs.

A meningioma, sometimes called a meningeal tumor develops from meninges, membrane coverings that surround the brain as well as spinal cord. Meningiomas normally have a sluggish growth rate. The tumors pressure on neighbouring tissue causes symptoms, which vary depending on the location. The majority of meningiomas, which make up around 30% of all brain tumors, may be successfully treated. In actuality, most of these tumors can be surgically removed, and many of them do not come back. Meningiomas have an unknown origin. The only recognised environmental health risk for meningiomas is radiation exposure, particularly during youth. Some cancers do not produce a tumor which is known as no tumor. Leukemias, the majority of lymphoma subtypes, and myeloma are some of them. Non-cancerous tumors can grow but will not migrate to other bodily regions also known as benign.

II. RELATED WORK

Raul-Ronald Galea et al., [3] proposed a research paper which examines the viability of using pilot datasets to apply all procedures first. The two segmentations that are the subject of this study are U-Net and DeepLabV3+. They gave information on developing and analysing essentially several model architectures, including Deep Lab, one of which wasn't specifically designed for medical image segmentation. Convolutional neural networks with standard classification are the foundation of U-Net. Two datasets are included, one of which is the imATFIB Dataset while the other is the ACDC Dataset. The ACDC challenge contains a range of 150 brief cine-MRI data from both the diastolic and systolic periods. 50 of the 100 are designated for testing, with the remaining 100 accessible for training and validation. The information was gathered as part of a clinical study conducted internally by imATFIB Dataset. A straightforward up sampling approach is used after a typical classification deep neural network as the foundation of DeepLabV3+. ResNet50 was employed as the deep neural network in this study.

Javeria Aminet al.,[4] The main objective of the research is to enhance the present CAD approaches by reducing user interaction, which will free up the time of medical professionals while reducing the likelihood of user error. The pre-treatment, segmentation, feature extraction procedures help to establish the significance of the recommended approach. Pre-processing options include PDDF, which has a considerable impact on improving the ROI and enabling more accurate segmentation of brain tumors. A neural technique based approach is used to distinguish among normal and the abnormal images, with just an accuracy rate of 83 percent. Fast Fourier transform with SVM is used to identify brain tumor with 98.9% accuracy rate. It uses a hybrid technique that combines seed growth process with fuzzy c means (FCM). The technique generates a 90 percent average score in tumor segmentation.

Farmanullah Jan et al., [5] This work presents an outstanding iris segmentation method. It initially employs an enhanced coarse-to-fine approach based on a programmable threshold to identify the iris inner boundary. Once modified, it can now recognise and mark eyelashes. The best coarse-to-fine marking technique is then used to define the iris outer border. The non-circular iris contour is then regularised using the Fourier series. Finally, the eyelids and those reflections are shown using the iris form. The Indian Institute of Technology Delhi developed IITD V1.0 (IITD). It will include 224 individuals' 1120 digital CMOS camera-captured eye images. It utilises near-infrared illuminators to gather images from IITD personnel and students. For IITD V1.0, the recognition accuracy is 98 percent. It is under the supervision of a Chinese Academy of Sciences' Institute of Automation. It includes 2639 eye images collected from those individuals using a closed-up iris camera made by CASIA. With this camera is a set of 8 circularly oriented illuminators are included. For the Chinese Academy of Sciences, the recognition accuracy is comprised at 99 percent. 460 eye images from 46 participants were gathered by the Malaysia Multimedia University (MMU) using LG cameras with the illuminators. Each of the participants receives a set of ten images to work. For MMU, the recognition accuracy is 97.86 percent.

Rohit Raja et al., [6] In this the wide-ranging application of the content-based image retrieval architecture in a range of domains is drawing the interest of many experts. The applicability of any of the CBIR structure is decided by that attributes obtained from a coloured image, and an unique CBIR technique is presented in this research. The Sobel and Canny approach is used in this study to first identify the region of interest in an image, after which the output is applicable to the human-visible HSV of that colour space. The neural network was used for classifying the data once it had been categorised using class labels. Discrete wavelet transformations are used to extract shade, edges, and other smaller characteristics in order to do this. Use the 4 shading models—RGB, HSV, YCbCr, and HSI—that is described in this article to extract information about a colour. The three qualities of texture, colour, and shape are combined to create a revolutionary approach that is discussed in this study. The steps in the algorithm are of image acquisition, which records images and then stores them, pre-processing, that will resizes the images and then stores them, ROI segmentation, which uses a variety of edge detection techniques, including Sobel and Canny, to identify the region of interest, and feature extraction, which is increasingly suited to human identification is HSV colour space.

Xue Feng et al., [7] This paper tells that they create a deep learning model for brain tumor segmentation utilising a 3D U-Net with modifications to the training and testing methods, network architectures, and model parameters. The BraTS challenge organisers provided the datasets used for this study, which include different-institutional clinically obtained pre-operative multi - modal MRI scans of glioblastoma and low-grade glioma that contain native (T1) , post-contrast T1-weighted , T2-weighted, and Fluid Attenuated Inversion Recovery volumes. Additionally, a linear model is developed based on the radiomics characteristics was established to highlight the clinical usefulness of the segmentation technique that was created. To predict patient overall survival, clinical characteristics and those obtained via segmentation are constructed. These improvements were evaluated and shown to have a high level of prediction accuracy in patients with both low-grade gliomas and glioblastomas, earning them first place in the 2018 BraTS competition.

Shidong Li et al., [8] The goal of this project is to create a novel deep learning method that uses regions of interest to automatically separate brain tumors in MRI images. There are two main phases in the approach. To minimise the impact of the disruption to normal tissue, the first step is to identify the tumor ROI using 2D networks with U-Net design. In step 2, a 3-dimensional U-Net is then used to partition tumors inside the chosen ROI. The suggested technique is tested using data from patients with 220 high-grade gliomas and 54 low-grade gliomas as part of the MICCAI BraTS 2015 Challenge. The novel region of interest aided cascaded network approach; they create more precise brain different-modal tumor segmentation technique. The approach can be a helpful tool for detecting, diagnosing, and arranging radiation treatments for brain cancer, according to numerical testing. The manual tumor contour and the one segmented by the suggested approach had Dice similarity coefficients and Hausdorff distances of 0.876 0.068 and 3.594 1.347 mm, respectively. These results show that the suggested approach is a reliable and practical tool for medical image processing and an efficient region of interest-aided deep neural network approach for the brain MR image tumor segmentation.

Ramin Ranjbarzadeh et al., [9] In this study, they first suggest a pre-processing technique to focus only on a tiny portion of the image instead of the whole part of the image in order to achieve an efficient as well as versatile segmentation of brain tumor. This approach will reduce computation time while resolving the over fitting issues in a Cascading Deep Learning model. While the second stage, a straightforward and effective Cascade Convolutional Neural Network is suggested because they are only working with a smaller part of each slice of the brain. This C-CNN model uses two alternative approaches to mine both locally and globally characteristics. Additionally, a new Distance-Wise Attention (DWA) method is developed to increase the segmentation accuracy of brain tumors in comparison with the state-of-the-art models.

III. METHODOLOGY

T1-weighted brain tumor dataset is shown in this work. These MR images were taken from the Kaggle dataset. There are 4,000 axial planed MRI images of meningioma, glioma, pituitary, and no tumor types of brain tumors. The dataset is initially divided into testing and training.

A: PREPROCESSING

In this pre-processing step, filter is applied for the removal of noise and resizing of the images is performed to get an enhanced images.

B: TUMOR LOCALIZATION AND SEGMENTATION USING MASK R-CNN

Our goal for segmentation is to automatically localise and separate the brain tumor from a complicated environment without the need for manual assistance. Utilizing the Mask RCNN, our goal is to identify tumor or non-tumor areas in the provided MR images.

C: FEATURE EXTRACTION

The necessary characteristics from the input images are extracted using the pre-defined CNN. ResNet 101 is taken into consideration in the implementation to extract more dependable and discriminating features. The final feature maps from the middle layer provide the region proposal network with a more accurate representation of the images at various sizes.

D: REGION PROPOSAL NETWORK

The feature map created by the previous technique will be sent to the RPN network, which will then produce ROIs. A 3x3 convolution operation provides crucial anchors that represent the bounding box in varying widths and are scattered over the whole picture using a sliding window to examine the image. There is about 20k correlating anchors of different sizes and scales across the image. Both classification technique and regression of bounding boxes are outputs of the RPN network. To determine if an anchor includes the item or not, binary classification is used. Regression using bounding boxes creates bounding boxes based on the value of intersection over union. A positive anchor, as opposed to a negative one, is one that will have an IoU greater than 0.7 and use the ground-truth box.

E: ROI POOLING:

Both the feature map and the planned ROI are inputs into this network. A deeper network than the RPN, the ROI pooling structure increases the size of the bounding box and categorises regions of interest, such as tumors or non-tumors. By modifying the bounding box's size and location, the bounding box regression (BBR) seeks to exactly encapsulate the tumor zone. The ROI boundaries often do not match the quality of the feature map since the feature map is down-sampled to within k dimensions of the original input image. The fixed-length features will be extracted to arbitrary candidate areas using the ROI Align layer, which will then be utilised to resize the feature maps.

F: SEGMENTATION MASK

The segmentation network creates a segmentation mask from positive regions of interest identified by the region of interest classifier that is represented by floating integers and contains more information than binary masks. The GT masks are shrunk in order to assess the loss with predicted mask throughout the training phase. The final output mask is created by scaling up the anticipated mask during inference to fit the ROI bounding box's specifications.

IV.RESULTS

The segmented regions (fig 2a, fig 2b, fig 2c) of the brain tumor MR images are shown in this section. In this study only T1-weighted MR images are taken into consideration. The suggested technique was developed using tensorflow and keras packages in python.

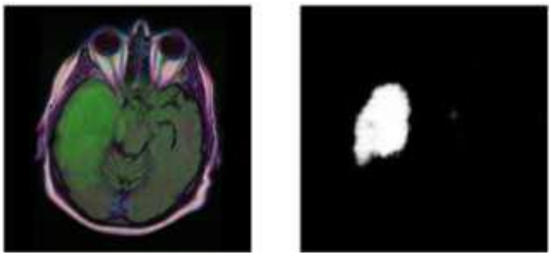

Fig 2a: Figure showing the segmentation of meningioma tumor

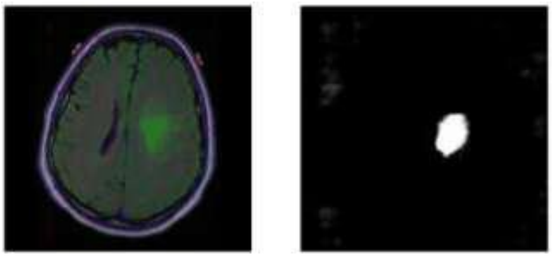

Fig 2b: Figure showing the segmentation of glioma tumor

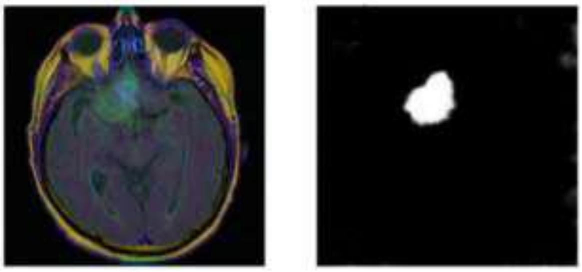

Fig 2c: Figure showing the segmentation of pituitary tumor

V.CONCLUSION AND FUTURE SCOPE

The segmentation of brain tumors from T1 weighted using an innovative technique based on CNN is shown in this work. The segmentation process is done using mask R-CNN which gives an accuracy of 94%. As a result, the suggested method would give medical facilities with a shortage of skilled personnel and resources greater diagnostic help. In the future work the automated approach can be focussed on T2 – weighted and FLAIR MR images of other planes that include coronal and sagittal plane slices. This implementation will help the doctors to identify the tumor easily using the above mentioned MR images.

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