

<sup>1</sup>Chintan Makwana  
<sup>2</sup>Hardikkumar Harishbhai  
 Maheta  
<sup>3</sup>Chauhan Pareshbhai  
 Mansangbhai

## Automated Segmentation of Brain Tumors in MRI: A Comprehensive Review of Deep Learning Approaches



**Abstract:** - The segmentation of tumor region from brain MRI images is challenging task. Automated approaches are necessary because manual segmentation takes a lot of effort and susceptible to inter-observer variability. This research provides an extensive analysis of deep learning methods for brain tumor segmentation from MRI data. The study begins with a summary of brain tumors and conventional segmentation techniques before doing a thorough evaluation of current developments in automated segmentation methods. We cover many deep learning architectures and their derivatives, specifically designed for brain tumor segmentation. The review also includes methods for differentiating between healthy brain tissue and aberrant tumor tissue. This paper critically examines the benefits, drawbacks, and potential applications of deep learning-based algorithms. It offers insights into current techniques and suggests future prospects for this important field of study.

**Keywords:** Brain tumor, segmentation, MRI, Deep learning

### I. INTRODUCTION

Because they significantly increase rates of morbidity and death, brain tumors are a major global health problem. Planning a course of therapy and tracking the disease's progression depend heavily on early and accurate identification as well as the exact demarcation of tumor borders. MRI provides excellent spatial resolution and soft tissue contrast, so it has become a helpful non-invasive method for evaluating brain malignancies.

Brain tumors are relatively rare compared to other types of cancer. However, they can occur at any age and are a major factor in the mortality of young people and children from cancer [1]. Cancer is the third-highest cause of mortality worldwide [2]. Due to their large contribution to global rates of morbidity and death, brain tumors represent a serious danger to public health. Variations exist in the occurrence of brain tumors based on age, gender, and geographic location. It is believed that there are between 10 and 15 instances per 100,000 individuals overall. Every year, primary brain tumors diagnosed in over 4,200 individuals in the United Kingdom. Approximately 1,300 deaths attributed to brain tumors each year in the USA [3]. According to the IARC, India experiences over 28,000 new instances of brain cancers each year, leading to more than 24,000 deaths annually [4].

The primary tumor arises in our brain. Primary tumors are frequently benign or cancerous. A secondary brain tumor is also known as a metastatic brain tumor. It occurs when cancerous cells from other organs, such as the lungs, breasts, skin, or kidneys, spread to the brain. Secondary brain tumors are always malignant (cancerous) [6]. The type of brain tumor, its location, the patient's age, and general health all have a significant impact on the tumor's survival rate. For instance, glioblastoma, a particularly aggressive kind of brain tumor, usually has a 5-year survival rate of fewer than 10%. In the diagnosis, planning, and follow-up of brain tumor therapy, medical imaging is significant. Early diagnosis of brain tumors is essential for improving the effectiveness of possible treatments and patient survival.

A brain tumor is a collection or mass of abnormal cells in the brain [1]. A brain tumor's shape, size, location, and metabolism may all be usefully revealed by medical imaging techniques like MRI, PET, and CT, which help in diagnosis. [6]. MRI is most suitable for imaging brain tumors. Different MR sequences such as T1-weighted, T1-with contrast weighted, T2-weighted, and FLAIR highlight various tumor subcomponents such as edema, necrosis, or contrast-enhancing core.

Brain MRI segmentation is a crucial process used in various aspects of neurology, including quantitative analysis, strategic planning, and functional imaging. The process of distinguishing and separating tumor tissues (active cells, necrotic core, and edema) from normal brain tissues (GM, WM, and CSF) is known as brain tumor segmentation [7]. The three primary types of brain tumor segmentation techniques are determined by the level of human participation needed: segmentation that is (1) manual, (2) semi-automated, and (3) completely automatic [8]. The manual segmentation of brain tumors from MR images is a labor-intensive, time-consuming task and subject to inter-observer variability. Semi-automatic methods involve a combination of computer and human knowledge, whereas fully automatic techniques just use computers to decide the segmentation—no human involvement is necessary. Deep learning algorithms have transformed medical image processing in recent years, and they provide potential possibilities for automating the segmentation process. In recent years, the development of reliable automatic segmentation techniques that can give accurate and objective segmentation has become an exciting and well-liked research area.

<sup>1</sup> \*Corresponding author: Assistant Professor, Department of Information Technology, Shantilal Shah Engineering College, Bhavnagar, Gujarat, India, Email: chmakwana@it.ssgec.ac.in

<sup>23</sup> Assistant Professor, Department of Information Technology, Shantilal Shah Engineering College, Bhavnagar, Gujarat, India  
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An extensive study of deep learning techniques for the automatic segmentation of brain tumors in MRI data is presented in this work. Convolutional neural networks (CNNs), in particular, have proven to be exceptionally adept in immediately learning complicated patterns from unprocessed image data, resulting in segmentation outcomes that are more precise and effective.

This review's main goal is to present a thorough examination of the most advanced deep learning techniques for brain tumor segmentation, taking into account each one's architecture, training methods, performance indicators, and clinical uses. This work attempts to emphasize the advantages and disadvantages of various deep learning models, spot new trends, and suggest future research areas by combining the results of previous studies.

We hope that this thorough study will further the continuing efforts to enhance automated brain tumor segmentation methods, which will ultimately lead to better neuro-oncology patient care, diagnosis, and treatment planning.

Deep learning approaches have demonstrated considerable promise in the realm of medical imaging analysis, particularly in the crucial job of brain tumor segmentation.

## II. RELATED WORK

The following are a few popular deep learning techniques for brain tumor segmentation:

### A. *Ensemble classification and segmentation for intracranial metastatic tumors on MRI images based on 2D U-nets [9]:*

The dataset used in this paper consists of MRIs collected from 1999 to 2018 to guide radio-surgical treatment with the Gamma Knife. This dataset includes the precise locations of 1872 metastatic lesions and information on 556 patients with cerebral. An unbalanced dataset of 23354 T1-weighted MRI images and 492 subjects with 904 tumors; each subject had an average of 48 images, and 20% of the subjects had tumors. The 512 x 512 pixel (or around 5 millimeters per pixel) and 3-millimeter-thick image format.

The first pre-processing stage consists of three steps: normalization, enhancement, and selection for the ROI. To correct the imbalance in pixel numbers between the skull and the backdrop, the active contour model is first used in the pre-processing stage to choose the ROI. Tenth, we strengthen the contract to support the image data. Due to the fluctuating picture size of ROI, we also resize the image. To eliminate noise in the MRI images, the form of the skull was delineated using the snake model, which leverages the forces and energy limitations in the image to separate the region of interest. Subsequently, the network was constructed using Keras framework, and the model was implemented using TensorFlow10 as the framework.

To identify decision points and display the ROC curve of the classification result, use the validation set. After that do the image segmentation on the tumor-containing images in the classified images, and then average the results in the validation set to discover the Mask c. This experiment can identify a specific amount of tumor since the validation set's AUC for the tumor volume bigger than 0.15 ml detection rate was 89.90%; a value of 0.8–0.9 indicates very strong performance. The PR curve is generated in order to ascertain the AUC of a tumor volume more than 0.15 ml. An F1-measure of 75.64% is obtained by classification result, whereas an IoU of 84.83% and a DICE score of 86.21% are obtained by the segmentation result. Cut down on the thirty minutes that it takes to hand label every patient to eighteen seconds.

### B. *Brain Tumor Segmentation Using Bit-plane and UNET [10]:*

In this paper for tumor segmentation, they combine the bit-plane technique with the U-Net architecture. Then, by identifying significant bits, they use Bit-Plane to split images into several images. Images containing important details were used for segmenting object boundaries. Three primary steps make up the image analysis process: tissue segmentation, object boundary segmentation, and pre-processing. The first U-Net groups 2D MRI images and then predicts the object boundary of the brain tumor. The second U-Net predicts each pixel's label inside the boundary by using its features.

They make use of 210 pre-operative MRI images of patients from the BraTS training dataset 2018. The recommended method is put into practice using the "Adam" optimizer, the "binary cross-entropy" loss in UNET, and the Keras library with TensorFlow as the backend. The technique was run on a Ge-Force GTX980 graphics card for a total of 50 epochs.

First, pre-process the data using normalization and slicing techniques. All four sequences of 3D brain MRI are combined into an axial slice to generate 2D brain slices. After obtaining the images, U-Net is used to segment the tumorous region from the background utilizing the input from the 2D images. After segmenting the tumor boundary, U-Net can segment the various types of tumors inside the boundary. The data that has passed the first stage of pre-processing is the input data. The technique performs with 82%, 68%, and 70% dice scores on validation data and 77%, 48%, and 51% dice scores on testing data for the WT, ET, and TC, respectively.

### C. *Deep learning with mixed Supervision for Brain Tumor Segmentation [2]:*

Mlynarski et al. [2] utilized the 2D U-Net model to segment gliomas, the most common primary brain tumors, in the BraTS 2018 dataset. They applied this model to both fully and weakly annotated datasets for tumor segmentation from brain scans. Their training dataset included fully annotated and weakly annotated samples. Employing a U-Net with an added branch for image-level classification, they combined pixel-level and image-level labels for training, addressing both binary and multiclass segmentation tasks. The adaptable 2D model accommodates various medical image types, including CT scan slices and multisequence MRI. They processed 300x300 dimension MRI images as input and expanded the U-Net architecture. The U-Net framework comprises an encoder and decoder path interconnected by concatenations to use low-level and high-level features. The final U-Net convolution layer provides pixel-wise classification scores, normalized using softmax during training. Batch normalization is implemented across all layers except the final one.

Experimental doing on 285 multimodal MRI subjects 2D MRI images with low-grade glioma or high-grade glioma. First, pre-process the data using skull-stripping and slicing. Resize the images into 240x240 dimensions. Segmentation model U-Net train on the high-grade gliomas MRI images. Then testing on high-grade gliomas and low-grade gliomas MRI images. Getting Dice score of whole tumors 0.87 and for core region 0.77 on fully annotated MRI images.

*D. Attention-Guided version of 2D U-Net for Automatic Brain Tumor Segmentation [11]:*

An attention mechanism technique works after concatenating low-level and high-level features. The method is the Multi-View Fusion technique, which allows us to leverage the 3D contextual data from input images while still using a 2D model. With some minor adjustments, the proposed network is based on the U-Net framework. There are two main pathways in it: the contracting path and the expanding path returns the original resolution. They replace the Max-pooling layers used in the original U-Net with convolutional layers with stride = 2, which correspond to the three levels of the down sampling of the contracting route. In the original U-Net, they also used residual units rather than plain units to expedite training and convergence. Two convolutional layers make up each residual unit. A residual unit is employed at the bottleneck to link the two paths after the contracting path. In the extending route, three residual units are also utilized. There are three upsampling layers in this approach, and each one doubles the size of the feature maps. Furthermore, each upsampling layer is followed by a 2x2 convolutional layer.

The BRATS 2017 and 2018 datasets were used for the studies in this research. These datasets training sets include 3D MRI volumes from 285 different patients, including 210 volumes that are HGG and 75 volumes that are LGG, both of which have 240x240x155 dimensions. The 3D MRI volume of 46 and 66 patients with unclear grades is included in the BRATS 2017 and BRATS 2018 validation sets, respectively.

They use the Google Colabory service to conduct all of our tests. TensorFlow backend is used in the development of our suggested network in Keras. By performing a 5-fold cross-validation on the 285 examples of the BRATS 2018 training set. Using an ensemble learning technique, assessment results for each view are finally obtained by averaging the Softmax output. The online evaluation platform computed all offered findings by analyzing our technique on standard validation datasets. For ET, WT, and TC, the average Dice scores produced by this model are 0.813, 0.895, and 0.823, respectively.

*E. DeepSeg: deep neural network framework for automatic brain tumor segmentation using magnetic resonance FLAIR images [12]:*

The FLAIR MRI data from the BraTS 2019 challenge used for this evaluation. The BraTS dataset includes 336 patients (resolution of 224x224) with gliomas that are heterogeneous from various institutions. Each patient undergoes four multimodal scans: T1 native, T1 post-contrast, T2, and T2-FLAIR. MRI data from 19 universities collected, employing diverse clinical regimens and scanner types.

Tensor Flow backend and the Keras library are used to implement the proposed models in Python. The networks are trained using a batch size of 16 and 35 epochs. After the feature extractor path, a spatial dropout with a rate of 0.5 was utilised during training. This straightforward regularisation technique helps prevent overfitting of the training dataset and promotes good generalisation of neural networks. A learning rate of 0.00001 has been used with the Adam optimizer. In this evaluation, 336 cases were designated for training purposes, with an additional 125 cases reserved for validation. The resulting segmentation outcomes demonstrated varying Dice scores spanning from 0.81 to 0.84, alongside Hausdorff distance scores ranging between 9.8 to 19.7. These findings underscore the efficacy of the developed methodologies in accurately delineating brain tumor boundaries, suggesting considerable promise for future clinical implementations.

*F. Brain tumor segmentation based on deep learning and an attention mechanism using MRI multi-modalities brain images [13]:*

To develop a robust brain tumor segmentation system, researchers introduce a novel preprocessing approach aimed at targeting specific regions within the image rather than processing the entire image at once. This strategy effectively addresses issues of overfitting within a Cascade Deep Learning model while significantly reducing computational overhead. Subsequently, a streamlined C-ConvNet is proposed for the segmentation task, capitalizing on its simplicity and efficiency, particularly suited for analyzing localized areas of brain slices. The C-CNN model incorporates two distinct methods to capture both local and global features essential for accurate segmentation. Additionally, to enhance segmentation accuracy beyond existing models, a novel Distance-Wise Attention (DWA) mechanism is introduced. This mechanism employs a multi-step process for tumor region identification within each slice, including the application of morphological operators to eliminate irrelevant areas, followed by steps such as reading and normalizing images from various modalities, binarization, and combining resultant areas to delineate tumor regions effectively.

In our study, we propose a cascade CNN model that integrates global and local information extracted from multiple MRI modalities. Additionally, we introduce a novel distance-wise attention mechanism designed to take into account the spatial distribution of brain tumors across four distinct input modalities. This mechanism effectively transfers essential location features of the image to the fully-connected layer, mitigating overfitting issues commonly encountered when employing numerous parallel convolutional layers, such as those in the self-co-attention mechanism.

Our pipeline was trained, validated, and tested using the BRATS 2018 dataset, which includes Multi-Modal MRI images along with patient clinical data featuring heterogeneous histological sub-regions, varying aggressiveness levels, and diverse prognoses. These Multi-Modal MR images, with dimensions of 240x240x150, were clinically acquired using different magnetic field strengths, scanners, and protocols across multiple institutions. The four MRI sequences utilized in the training, validation, and testing phases are FLAIR (highlighting fat regions), T1 with gadolinium-enhancing contrast (highlighting water sites), T2 (or T2-weighted), and T1 (or T1-weighted).

The dataset comprises 210 cases of High-Grade Gliomas (HGG) and 75 cases of Low-Grade Gliomas (LGG), randomly partitioned into training data (80%), validation data (10%), and test data (10%). Neuroradiologists annotated the images with tumor labels, where numbers 1, 2, 3, and 4 denote necrosis, edema, non-enhancing tumors, and enhancing tumors, respectively, while a score of 0 represents normal tissue.

Extensive testing conducted on the BRATS 2018 dataset illustrates the competitive performance of the proposed model. Specifically, the method achieves mean dice scores of 0.9203, 0.9113, and 0.8726 for the overall tumor, enhancing tumor, and tumor core, respectively. These results underscore the effectiveness of the suggested approach in accurately segmenting brain tumors across various regions.

G. *Automated Detection of Brain Tumor through Magnetic resonance images using convolutional neural network [3]:*

The proposed model, findings from experiments, and a comparison analysis are all presented in this part. Three datasets the BraTS 2018, the BraTS 2019, and the BraTS x2020 patient data for brain tumors were used to evaluate our proposed segmentation and classification model for brain tumors, and we achieved higher performance. Each patient has four different MR imaging modalities (T1, T2, T1CE, and FLAIR). To segment and classify brain tumors using the BraTS dataset, our proposed model was also compared to other segmentation and classification methods, such as AFPNet, CRFs, VGG-16, 3D-Dense UNets, GLCM, and T-test approach.

Their MR imaging data was separated into training, validation, and testing sets. The proposed system is trained using an Adam optimizer with a minibatch size of 30, a learning rate of 0.001, and data randomized between iterations. The weights of the convolutional layers in this work are initialized using a Glorot initializer, also known as a Xavier initializer. Accuracy, specificity, recall, precision, and dice score are the five performance matrices that are used to assess performance. With the suggested model, these performance matrices required 33 minutes and 19 seconds of training time. The training time for our suggested model is assumed to be 99.95 seconds on average per epoch.

First, preprocess the MR images using a median filter, then use skull stripping to remove the skull porting from the MR images. Skull stripping is done to isolate intracranial non-brain material from the brain. Next, the suggested approach for brain tumor segmentation is implemented using the three-time convolution layer, batch normalization, two-time max-pooling, and four-time rectified linear unit (ReLU) as an activation layer in the segmentation technique. To extract the features from MR pictures, a first convolution layer was applied, with a filter (kernel) size of  $64 \times 3 \times 3$ , stride [1 1], and padding [1 1 1]. Batch normalization was used after the convolution layer to reduce the weight power of the highly biased nodes, offer regularization, accelerate learning, normalize pixel values, prevent overfitting, and speed up the model. The postprocessing procedure was used to improve the structural segmentation results after the MR image segmentation. Following segmentation, they classified MR images using the CNN architecture GoogleNet.

The outputs of the suggested framework for categorizing and dividing brain tumors. The suggested method produced minimum batch accuracies of 95%, 96.50%, and 98% and maximum batch accuracies of 96.50%, 97.92%, and 98.79% for the BraTS 2018, BraTS 2019, and BraTS 2020 datasets. The suggested method achieves an average accuracy of 96.50% for the BraTS 2018 dataset, 97.50% for the BraTS 2019 dataset, and 98.00% for the BraTS 2020 dataset. Similar to this, the suggested method for classifying brain tumors exhibits average accuracy levels of 96.49% for photos from the BraTS 2018 dataset, 97.31% for images from the BraTS 2019 dataset, and 98.79% for the BraTS 2020 dataset.

### III. RESULTS

| Paper                       | Model  | Dataset                       | Subject (Size)   | Model Configuration  | Evaluation   |
|-----------------------------|--|-------------------------------|--|--|--|
| Mlynarski et al. [2]        | mixed supervision method   | BraTS 2018                    | 285 (240x240)  | optimizer: Adam<br>Loss: Binary cross entropy<br>Convolution: 3x3<br>Activation: ReLu<br>Max Pooling: 2x2                    | Dice Score<br>WT = 0.87<br>TC = 0.77                                   |
| Gull et al. [3]             | 2D U-netbased, GoogleNet   | BraTS 2018, 2019, 2020        | Training 998 & 1173<br>Validation 142 & 167<br>(240x240) | Batch size:30<br>optimizer:Adam<br>learning rate:0.001<br>Loss: --<br>Convolution:3x3<br>Activation:ReLu<br>Max Pooling: 2x2 | Dice Score<br>BraTS2018 = 0.96<br>BraTS2019 = 0.97<br>BraTS2020 = 0.98 |
| Li, Cheng-Chung, et al. [9] | 2D U-Net, 2D-UNet + VGG-16, 2D-UNet + ResNet-34, 2D-UNet + EffcientNet | Gamma Knife from 1999 to 2018 | 556 (256x256)  | optimizer: Adam<br>Loss: Binary cross entropy<br>Convolution: 3x3<br>Activation: ReLu<br>Max Pooling: 2x2                    | Dice Score = 0.86<br>IOU = 0.84  |
| Tuan et al. [10]            | U-net + Bit-plane  | BraTS 2018                    | HGG 210, LGG 75 (176x176)                                | optimizer: Adam<br>Loss: Binarycross entropy<br>Convolution:3x3<br>Activation:ReLu   | Dice Score<br>WT= 0.77<br>TC =0.51<br>ET= 0.48                         |
| Noori et al. [11]           | 2D U-net + attention-guided  | BraTS 2018, 2017              | HGG 210, LGG 75 (240x240)                                | optimizer: Adam<br>Loss: Cross entropy<br>Convolution: 2x2<br>Activation: PReLU<br>Max Pooling: 2x2                          | Dice Score<br>WT = 0.895<br>TC = 0.823<br>ET = 0.813                   |

|                          |                                     |            |   |   |                                      |
|--------------------------|-------------------------------------|------------|---|---|--------------------------------------|
| Zeineldin et al. [12]    | 2D U-Net                            | BraTS 2019 | Training 270<br>Validation 66 (224x224) | Batch size: 16<br>optimizer:Adam<br>learning rate:0.00001<br>Loss: Weighted cross entropy<br>Convolution:3x3<br>Activation:ReLu<br>Max Pooling: 2x2 | Dice Score = 0.84                    |
| Ranjbarzadeh et al. [13] | Deep learning + attention mechanism | BraTS 2018 | HGG 210<br>LGG 75 (240x240)             | Batch size: 2<br>optimizer:Adam<br>learning rate:0.0001<br>Loss: Crossentropy<br>Convolution:3x3<br>Activation:ReLu<br>Max Pooling: 2x2             | Dice Score<br>WT = 0.92<br>TC = 0.87 |
| Ronneberger et al. [14]  | U-net + RES + WC                    | DIC-He La  | 20 (240x240)                            | optimizer: Adam<br>Loss: Binary cross entropy<br>Convolution: 3x3<br>Activation: ReLu<br>Max Pooling: 2x2   | IOU = 0.77                           |

#### IV. CONCLUSION AND DISCUSSION

Deep learning approaches have revolutionized brain tumor segmentation by providing accurate, efficient, and scalable solutions. In this comprehensive review, we have examined various deep learning techniques employed for this purpose. This paper provides a thorough analysis of various deep learning (CNN) based U-Net models for brain tumor segmentation from brain magnetic resonance images (MRI). According to the analysis, deep learning-based approaches (CNN, U-Net) were employed to segment brain abnormalities. These networks leverage hierarchical feature learning to effectively delineate tumor boundaries. Attention mechanisms have further improved segmentation accuracy by focusing on relevant regions of the input image. Multi-scale and multi-modal approaches have enhanced performance by capturing information at different resolutions and leveraging complementary imaging modalities. The quantitative analysis using various evaluation criteria and segmentation approaches helps in the accurate diagnosis of tumors and helps researchers identify new routes for future study. The study primarily used various datasets by the researchers, like MICCAI (Medical Image Computing and Computer Assisted Intervention) Challenge on Multimodal Brain Tumor Image Segmentation Benchmark (BraTS) 2018–2020, for result validation. Despite the remarkable progress, several challenges persist, including the need for large and diverse datasets, robustness to imaging artifacts, interpretability of model predictions, and generalization to diverse patient populations. Future research directions may focus on addressing these challenges through techniques such as data augmentation, domain adaptation, uncertainty estimation, and model explainability. In conclusion, deep learning approaches have significantly advanced automated brain tumor segmentation in MRI scans, offering unprecedented accuracy and efficiency. Continued research and innovation in this field hold the potential to further improve clinical outcomes and empower healthcare practitioners in the diagnosis and treatment of brain tumors.

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