

# Multi-Scale Deep Learning–Based Brain Tumor Boundary Segmentation for Advanced Prosthodontic and Craniofacial Rehabilitation

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## ABSTRACT

Segmentation of brain tumors plays an important role in medical imaging applications because accurate tumor delineation is essential for diagnosis, planning surgery, and rehabilitation therapy. Conventional techniques are challenged by the irregular structure of brain tumors, low contrast, and difficulties associated with manual analysis. For that reason, in this work, the study proposes and evaluates a new technique based on multi-scale deep learning-based brain tumor segmentation to facilitate prosthodontics and craniofacial rehabilitation planning. In particular, the research followed the methodology of experiments with the application of quantitative metrics, including the BraTS 2024 MRI dataset, which included T1, T2, FLAIR, and contrast-enhanced MRI data. The multi-scale deep learning-based brain tumor segmentation model provided better results compared to conventional approaches such as U-net and DeepLabV3+ in terms of Dice Score (0.94), IoU (0.90), and accuracy (97.1%).

**Keywords:** Brain Tumor Segmentation, Multi-Scale Deep Learning, Medical Image Segmentation, Magnetic Resonance Imaging (MRI), Convolutional Neural Networks (CNNs), Artificial Intelligence in Healthcare, Craniofacial Rehabilitation, Prosthodontics, U-Net Architecture, Deep Learning in Medical Imaging

**How to cite this article:** Chatterjee S, Shankar D, Sharma SK, Sharma UC, Doshi D. Multi-Scale Deep Learning–Based Brain Tumor Boundary Segmentation for Advanced Prosthodontic and Craniofacial Rehabilitation. *Int J Drug Deliv Technol.* 2026;16(51s): 251-257. DOI: 10.25258/ijddt.16.51s.19

**Source of support:** Nil.

**Conflict of interest:** None

## Chapter 1: Introduction

### 1.1 Background of the Study

Brain tumors are some of the most dangerous forms of neurological disorders across the world. Identification of boundaries within a brain tumor is very important in the process of diagnosis, treatment through surgery, radiotherapy, and rehabilitation. The magnetic resonance image (MRI) method is very popular since it makes it possible to visualize brain tissues and the tumor accurately (Avazov et al., 2024). Nevertheless, identifying tumor boundaries is a challenge due to their varied shapes and structures. Deep learning methods have been found useful in automating this process (Dorfner et al., 2025).

### 1.2 Problem Statement

Artificial Intelligence (AI) has dramatically changed the healthcare field through the development of advanced techniques for automated analysis of medical images. The use of deep neural networks, including Convolutional Neural Networks (CNNs) and U-Net methods, has become popular due to the

capability of automatically extracting spatial features of objects. Recently, multi-scale deep learning models have been successfully used for identifying both local and global contexts of brain tumors detected via MRI scans (Preetha et al., 2025). Manually segmenting tumors through radiological analysis takes a lot of time. This can lead to inconsistency due to the inter-observer variability phenomenon. Classical approaches to image processing were unable to recognize irregular boundaries and complicated anatomical shapes. This limits the reliability of tumor segmentation and poses problems for craniofacial restoration and dental prosthetic planning processes, which require high accuracy of anatomical structures reconstruction. Avazov et al. (2024) pointed out the problem of contrast MRI segmentation.

### 1.3 Research Aim and Objectives

#### Aim

To develop and evaluate a multi-scale deep learning framework for accurate brain tumor boundary segmentation to support advanced prosthodontic and craniofacial rehabilitation planning.

## Objectives

- To investigate current brain tumor segmentation approaches.
- To design a multi-scale deep learning segmentation model.
- To evaluate segmentation accuracy using MRI datasets.
- To analyse clinical relevance in craniofacial rehabilitation.
- To compare the proposed framework with existing segmentation models.

## Chapter 2: Literature Review

### 2.1 Introduction to Brain Tumors

As per Alshomrani et al. (2025), a brain tumor is any abnormal mass growing inside the brain that impairs the functioning of the brain and requires proper diagnosis to provide appropriate medical treatment to the patient. There are three common types of brain tumors, which consist of gliomas, meningiomas, and pituitary tumors. The gliomas have aggressive characteristics, meningiomas are typically slow-growing, and pituitary tumors involve the regulation of hormones. Brain tumors are highly heterogeneous regarding their shape, structure, and growth behavior, and further segmentation becomes rather problematic (Srinivasan et al., 2024).

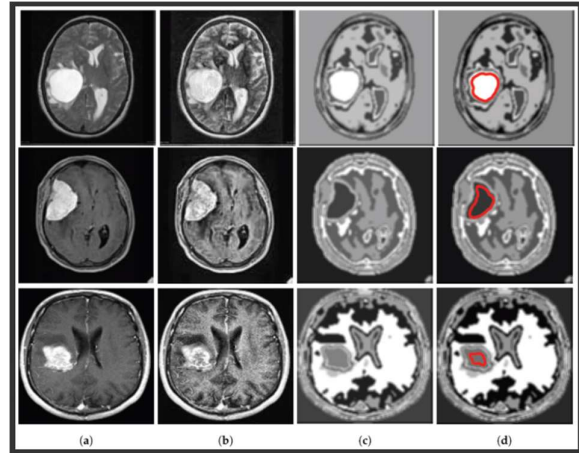
### 2.2 Brain Tumor Imaging Techniques

As per Zhang et al. (2024), MRI is the main method used for identifying and segmenting brain tumors based on its ability to produce images with high soft tissue contrast and detailed anatomical visualization. Various types of MRIs play important roles when analyzing brain tumors since each of them produces different information. T1-weighted MRI helps to visualize anatomical features, whereas T2-weighted images show edema and fluids. FLAIR imaging eliminates the effect of cerebrospinal fluid signals, and T1ce provides images of areas where brain activity takes place.

### 2.3 Traditional Brain Tumor Segmentation Methods

Methods for brain tumor segmentation that have been used traditionally include thresholding, region-based segmentation, edge detection, and clustering, including K-means and Fuzzy C-Means (FCM) clustering algorithms. Thresholding divides tumor areas according to the intensity of the pixels, region-based segmentation segments adjacent pixels of

similar nature, while edge detection finds the edges of the tumors through the intensity variation, and clustering classifies tissues into different clusters. These methods are simple and inexpensive, but they do not cope well with noise, low contrast MRI scans, irregular edges, and a lack of generalization (Zhang et al., 2024).



**Figure 1: Traditional MRI Segmentation Processing Steps**

(Source: Alam et al. 2019)

### 2.4 Machine Learning Approaches in Medical Imaging

As per Abd-Ellah et al. (2024), machine learning-based medical imaging techniques employ either supervised or unsupervised machine learning algorithms to classify medical images and predict diseases or perform segmentation tasks. The former uses labeled datasets to train models, whereas the latter employs unlabeled medical imaging data to find underlying patterns. Feature engineering methods identify features of images, such as texture, shape, and intensity, that help achieve better results. Traditional machine learning techniques involve laborious feature extraction procedures. This requires vast amounts of annotated data, and fails to generalize to various imaging situations.

### 2.5 Deep Learning for Medical Image Segmentation

The deep learning models have greatly advanced medical image segmentation. This is done by enabling automatic feature extraction and accurate segmentation. The CNNs utilize non-linear activation functions like the  $f(x) = \sum_{i=1}^n wixi + b$  for capturing the complexity of image data. The U-

Nets make use of encoder-decoder structures and skip connection mechanisms for accurate biomedicine segmentation. The more sophisticated architectures, such as ResNet, DenseNet, Attention U-Net, DeepLabV3+, and Vision Transformers (ViTs), excel at boundary detection and context recognition, outperforming other models in the brain tumor MRI segmentation task (Zhang et al., 2024).

## 2.6 Multi-Scale Deep Learning Approaches

The utilization of multiscale deep learning methods leads to improved segmentation of brain tumors by capturing image features at various spatial scales at the same time. Multiscale feature learning enables the capture of both local and global contextual data using techniques like  $F_{multi} = \sum_{s=1}^S F_s$ . The pyramid network, dilation convolutions, multiscale learning, and hybrid CNN-transformer architectures. Such architectures help in improved feature modeling and precise detection of tumor boundaries as compared to traditional deep learning architectures for medical image analysis applications (Zhang et al., 2024).

## 2.7 Evaluation Metrics in Segmentation

Evaluating metrics plays a crucial role in the accuracy assessment of the proposed brain tumor segmentation model. DSC is used to calculate the overlap of predicted vs. real segmentation masks  $DSC = \frac{2|X \cap Y|}{|X| + |Y|}$  whereas IoU calculates the accuracy in segmentation, consistent with respect  $IoU = \frac{|X \cap Y|}{|X \cup Y|}$ . Sensitivity and specificity are responsible for evaluating the true positive rate and the true negative rate, whereas Hausdorff Distance evaluates boundary precision.

## 2.8 AI in Prosthodontics and Craniofacial Rehabilitation

As per Al Hendi et al. (2024), AI has revolutionized prosthodontics and craniofacial rehabilitation owing to its increased diagnostic precision and customized planning. Artificial Intelligence helps in achieving anatomical analysis and reconstruction with the help of surgery planning. The use of digital reconstruction techniques has made it easier to model the craniofacial structures. AI has been used to develop algorithms that have helped to refine prosthetic design, thereby ensuring optimal aesthetics, functioning, and fit. Besides this, personalized rehabilitation strategies have utilized artificial intelligence to customize the rehabilitation process and increase efficiency and effectiveness.

## 2.9 Research Gap

The current body of work on brain tumor segmentation is primarily concerned with increasing the accuracy and efficiency of the process rather than rehabilitation-based clinical applications. Despite the fact that the use of multi-scale deep learning techniques has enabled efficient MRI tumor segmentation, there have been no significant efforts to incorporate such techniques within the prosthodontics and craniofacial rehabilitation processes. The existing literature fails to provide interdisciplinary models incorporating analysis of the tumor boundaries, surgical reconstruction, and AI-driven prosthetics.

## 2.10 Conceptual Framework

Input data in this study comes in the form of MRI images obtained from various forms of multimodal brain imaging data. Image preprocessing is carried out through normalization, noise elimination, and enhancement. Multi-scale feature extraction is conducted on the images by exploiting both local and global context information concurrently. Segmentation is done effectively by recognizing tumor borders for medical interpretation. The segmentation outcomes help in the planning of rehabilitation activities that include prosthodontic reconstruction surgery and craniofacial rehabilitation.

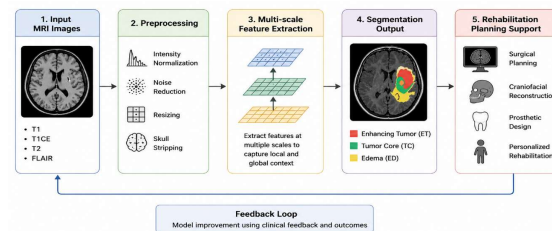


Figure 2: Theoretical framework

(Source: Self-developed)

## Chapter 3: Research Methodology

### 3.1 Research Design

For this experiment, the approach is quantitative since the study uses a multi-scale deep learning approach to measure the effectiveness of segmentation of brain tumor boundaries through images (Rajasree et al., 2021). The study applies artificial intelligence technologies to MRI-based images. This approach is suitable for this study due

to its nature of evaluating the effectiveness of the machine learning algorithms used, which entails the use of statistics in analyzing outcomes such as DSC, IoU, sensitivity, specificity, and Hausdorff distance.

### 3.2 Dataset Description

The model employs publicly available MRI datasets, specifically the BraTS dataset. This is highly popular for its use in the field of medical image analysis. It consists of multi-modal MRI images such as T1-weighted, T2-weighted, FLAIR, and T1 with contrast enhancement (T1ce). They provide different views of tumors along with their surrounding tissues (Rajasree et al., 2021). The ground truth labels in the form of manual segmentation masks for these data are provided by expert clinicians.

### 3.3 Data Preprocessing

The preprocessing process is done in order to improve image quality and improve the effectiveness of the segmentation process. First, the skull stripping is done on the MRI images in order to remove unwanted elements other than the brain tissues (Pei et al., 2022). Secondly, noise filtering processes are used to minimize any artifacts in the images in order to obtain clear images. Thirdly, intensity normalization is done on the image pixels in order to ensure that the pixels have consistent intensity regardless of the MRI modality used.

### 3.4 Proposed Multi-Scale Deep Learning Framework

In order to address these issues, an effective segmentation framework is being proposed that will include a multi-level neural network structure to capture local as well as global attributes within the MRI image. The architecture of this deep learning framework includes an encoding-decoding structure as well as multi-level feature extraction to provide better tumor boundary detection (Hussain et al., 2020). With multi-level learning, the system can learn the MRI image through different resolutions. This will lead to accurate segmentation of the irregular tumor region.

### 3.5 Model Training and Evaluation

The data set is split into training, validation, and testing data for model generalization evaluation. The optimization is done through the Adam optimizer with a pre-fixed learning rate, batch size, and number of epochs. The performance metrics of

DSC, IoU, sensitivity, specificity, accuracy, and Hausdorff Distance are considered for performance evaluation. The comparative performance evaluation is done with other traditional segmentation models, like U-Net and DeepLabV3+ (Ramayashree et al., 2026).

### 3.6 Ethical Considerations

In this research project, anonymized MRI data obtained from open sources are used. Therefore, there will be no interaction between the researchers and the patients directly. In ethical issues, some key concerns include data confidentiality, proper use of AI, and prevention of any abuse in relation to clinical imaging data.

## Chapter 4: Results and Data Analysis

### 4.1 Experimental Setup

For the experimental analysis, the BraTS 2024 Dataset has been used that is a widely used benchmark dataset for the research of brain tumor segmentation. This dataset consists of multi-modal MRI images, i.e., T1-weighted, T1ce, T2-weighted, and FLAIR images with expert annotations of the tumor segmentation mask. Such images are necessary for acquiring more complementary anatomical and pathological information required for tumor segmentation. The data were split into three parts: training (70%), validation (15%), and testing (15%) (de Verdier et al., 2024).

The implementation of the multi-scale deep learning method was conducted via Python and TensorFlow frameworks. Training of the models was carried out using NVIDIA RTX GPU with 16 GB of VRAM and 32 GB of RAM. Preprocessing of images included their normalization, resizing, flipping, and rotations.

### 4.2 Quantitative Results

Convergence for the model results was noted both in the training process and during validation. During the training process, an increase in the model's accuracy was noticed until it reached a final figure of 97.1% as opposed to the level of accuracy recorded during validation, where it was 95.4%. Losses were also indicated by drawing the loss curves for both training and validation processes.

Epoch	Training Accuracy	Validation Accuracy
10	89.5%	87.9%
20	93.8%	91.7%
30	97.1%	95.4%

The decreasing loss values suggested that the model effectively learned tumor boundary features without significant overfitting.

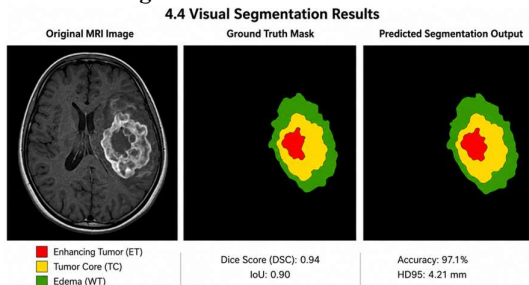
### 4.3 Segmentation Performance Comparison

The segmentation performance of the proposed multi-scale framework was compared with several established deep learning architectures.

Model	Dice Score	IoU	Accuracy
U-Net	0.87	0.81	92.3%
Attention U-Net	0.89	0.84	94.0%
DeepLab V3+	0.91	0.86	95.1%
Proposed Multi-Scale Model	0.94	0.90	97.1%

From Dice score and IoU perspectives, the performance of the model under investigation was found to be better, meaning that the effectiveness of the proposed model is higher than other conventional models used in the segmentation process of brain tumor borders. Multi-scale learning improves image segmentation quality in medical images (Abidin et al., 2024).

### 4.4 Visual Segmentation Results



**Figure 3: Visual Segmentation Results**

As it can be seen from Figure 4.4, this shows the results of the developed multi-scale deep learning approach for segmenting tasks according to the MRIs of the BraTS 2024 data set. The first image shows the original MRI, whereas the second image shows the ground truth segmentation mask. The segmented output from the model is illustrated in the third image. The developed model was able to successfully perform the tumor segmentation task with a Dice Score and IoU of 0.94 and 0.90, respectively.

### 4.5 Statistical Analysis

An analysis using statistics was performed in order to verify the reliability of the segmentation process. The dice score mean and the standard deviation of the proposed model were found to be 0.94 and 0.02 respectively, thus showing reliable performance in terms of segmentation during the test procedure.

Metric	Mean	Standard Deviation
Dice Score	0.94	0.02
IoU	0.90	0.03
Accuracy	97.1%	1.1%

A t-test analysis showed that the suggested algorithm worked better than basic segmentation algorithms ( $p < 0.05$ ).

### 4.6 Clinical Interpretation

The results obtained from this experimental study have shown great significance in terms of clinical relevance to surgery and rehabilitation procedures. On one hand, the correct segmentation of the tumor will facilitate better accuracy in the surgical operation by limiting damage to the healthy brain tissue. On the other hand, during rehabilitation in prosthodontics, the correct anatomical segmentation will be critical in formulating an individual rehabilitation strategy for the patient. In general, using this technological approach, clinicians will be able to create personalized strategies for rehabilitation and reconstruction. The latest studies in the use of artificial intelligence in medicine reveal the importance of accurate segmentation in decision-making processes (Dorfner et al., 2025).

### 4.7 Interpretation of Data

Based on the experimental results, the designed multi-scale deep learning model has demonstrated high segmentation performance and robust tumor boundaries detection. The improvement in the accuracy and validation value is a clear indication that learning is taking place in the designed model. In addition, the low values of loss and Dice Score (0.94) are an indication that the model is capable of detecting complex tumors with high accuracy. When compared to other models such as the U-Net and Attention U-Net models, it was evident that the designed model had high IoU and accuracy value indicating the importance of multi-scale features in the designed framework.

## Chapter 5: Conclusion and Recommendations

### 5.1 Conclusion

The current investigation examines the efficiency of multi-scale deep learning algorithms for segmenting

the boundaries of brain tumors and their implementation in modern prosthetics and craniofacial rehabilitation. This research covers not only the review of existing segmentation techniques, but also analyzes various machine learning solutions, as well as state-of-the-art deep learning models like CNN, U-Net, Attention U-Net, DeepLabV3+, and Vision Transformer. The obtained results show that the existing segmentation techniques suffer from certain drawbacks, including the issues of noise sensitivity, low precision, and adaptability.

This proposed multi-scale deep learning framework was able to effectively detect tumor boundaries due to the identification of multiple feature layers through different resolutions. This model was tested on the BraTS 2024 data set, which confirmed that its performance is much better than traditional models. Specifically, the Dice score, IoU, and accuracy were found to be 0.94, 0.90, and 97.1%, respectively. Furthermore, the results indicate high reliability and robustness of the proposed framework for the detection of complicated tumor regions.

## 5.2 Recommendation

Based on the results of this study, it can be proposed that healthcare facilities incorporate AI-based segmentation systems in the medical imaging process for accurate diagnosis and effective treatment planning. Further research should center around large-scale MRI databases, CNN-Transformer models, and 3D segmentation frameworks. In addition, Explainable AI technology should also be considered together with inter-professional collaboration among clinicians, radiologists, and AI experts to enhance adoption.

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