

3D Multimodal Image Segmentation For Detection Of Brain Tumor

Project Report submitted by

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Certificate

This is to certify the mini project entitled “3D Multimodal Image Segmentation For Detection Of Brain Tumor” submitted by Bedre Dhanush (Roll No. 420113), Vallamkondu Sai Varun (Roll No. 420246), Velagana Nataraj Gowd (Roll No. 420250) to National Institute of Technology, Andhra Pradesh as a part of third year second semester is a record of bonafide work carried out by them under my supervision and guidance. This work has not been submitted elsewhere for any purpose.

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Chapter 1

Introduction

Brain Tumors are considered to be a highly significant and life-threatening condition, having various types of complexities which require more attention for accuracy on detection and classification. Medical imaging plays a significant role in the diagnosis and most helpful in treatment of brain tumors [33]. Magnetic resonance imaging (MRI) is mostly used for detecting tumors. However, especially for 3D images in MRI manual analysing images are very much time-consuming and challenging task. Deep learning techniques, specifically convolutional neural networks (CNNs), have exhibited promising outcomes in numerous medical image analysis assignments [39], including the segmentation of brain tumors. The U-Net architecture, introduced in 2015, has become a popular choice for medical image segmentation due to its ability to handle small training datasets and capture both local and global image features.

In this project, we aimed to explore the effectiveness of different U-Net variants for 3D MRI brain tumor segmentation using the BraTS 2020 dataset. We started with the basic U-Net architecture and progressed to more advanced variants, including 3D U-Net and U-Net++. Our goal was to evaluate the performance of these architectures and identify the most effective one for automated brain tumor segmentation.

Chapter 2

Literature Review

Various approaches have been proposed for brain tumor segmentation using diverse forms of medical images such as Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) scans. This review summarizes the current state-of-the-art and also some traditional techniques for brain tumor segmentation using MRI images.

Machine learning-based techniques have also been introduced for brain tumor segmentation. These techniques include supervised and unsupervised learning methods. In supervised learning, a model is trained on labeled data to classify the tumor region from the background. Support Vector Machines (SVMs), Random Forests (RFs) and K-Nearest Neighbors (KNN) are commonly used supervised learning algorithms for brain tumor segmentation. Unsupervised learning, on the other hand, does not require labeled data, but relies on clustering techniques to segment the image.

Deep Learning techniques have recently gained popularity in medical imaging especially in the segmentation tasks, particularly Convolutional Neural Networks (CNNs). U-Net, a deep learning architecture specifically designed for medical image segmentation, has been widely used for brain tumor segmentation. U-Net combines a contracting path, similar to a typical CNN, with an expansive path to localize and segment the tumor accurately.

In conclusion, brain tumor segmentation presents a significant challenge given the complexity and variability of brain tumors. While various approaches have been proposed, deep learning-based techniques, particularly U-Net, have shown promising results and its variants are also emerging as the leading approach for segmenting brain tumors in MRI images

Chapter 3

Methodology

The methodology for this project involved several steps, beginning with the collection and preparation of data. The BraTS 2020 dataset was selected for its size and diversity, containing 3D MRI scans of patients with class wise brain tumors regions, along with ground truth segmentations of tumor regions. The flow chart in Figure 1 outlines the subsequent steps of the methodology.

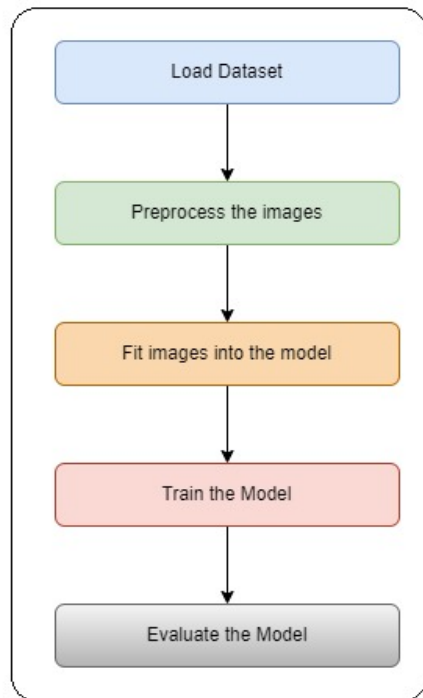


Figure 3.1: Workflow

3.1 Data Pre-Processing

The images are initially provided in .nii format and need to be standardized before being used for model training. The steps involved in this phase are shown in Figure 2, the block resize images involves the process of subtracting the mean of the image slice and then followed by the division with the standard deviation, if it is not zero. This is performed for each slice of the 3D image volume along the z-th dimension. The resulting centered and scaled image slice is then saved into a standardized image volume, which has the same shape as the original image volume. This process is necessary to ensure that the model is able to learn from the data effectively and to prevent any potential issues with numerical instability during training. After standardizing the images, they are sliced in such a way that the resulting input size is (128,128,128,4).

3.2 Proposed model architecture

The 3D U-Net architecture used in this task is designed for 3D image segmentation. It comprises of an encoder and decoder network with the skip connections, and is based on the original 2D U-Net architecture [18]. A pictorial representation of this architecture is depicted in Figure 3. The encoder contains four convolutional blocks that consists of an ascending number of filters 16, 32, 64, and 128 with each block followed by max pooling and dropout layers. The each convolutional block contains two 3D convolutional layers with the equal number of filters, subsequently then batch normalization, used to improve the performance and stability of the neural network and ReLU activation. We chose the ReLU activation function in our work due to its computational efficiency, making it particularly well-suited for use in deep neural networks that contain numerous layers. Additionally, ReLU helps mitigate the issue of vanishing gradients that can occur in networks with deep architectures that use sigmoid or tanh activation functions. The bottleneck layer has 256 filters, and the decoder comprises four transpose convolutional layers with decreasing number of filters. Each decoder block is followed by the concatenation with its corresponding encoder layer and a convolutional block with dropout. The final layer is a softmax activation convolutional layer with output size set to 4 for 4 output channels, corresponding to the 4 classes. The model's input size is 128x128x128x4, while its output size is also 128x128x128x4.

3.3 Training phase

Throughout the training phase, we employed the Adam optimizer, a preferred technique due to its quick convergence and ability to handle noisy gradients with robustness. To address memory constraints, we employed a Keras Data Generator to load images in batches, enabling efficient utilization of available memory resources and smooth model training on the dataset. Our hardware setup consisted of two NVIDIA T4 GPUs on the Kaggle platform. To enhance the performance of the model during training, we utilized callbacks to dynamically adjust the learning rate and save the model weights at the conclusion of each epoch. Our implementation employed two callbacks, namely ReduceLROnPlateau, which monitored the validation loss during training and reduced the learning rate by a factor of 0.2 with patience attribute value set to 2 and ModelCheckpoint. To evaluate the model's performance, we employed several metrics at each epoch, including accuracy,

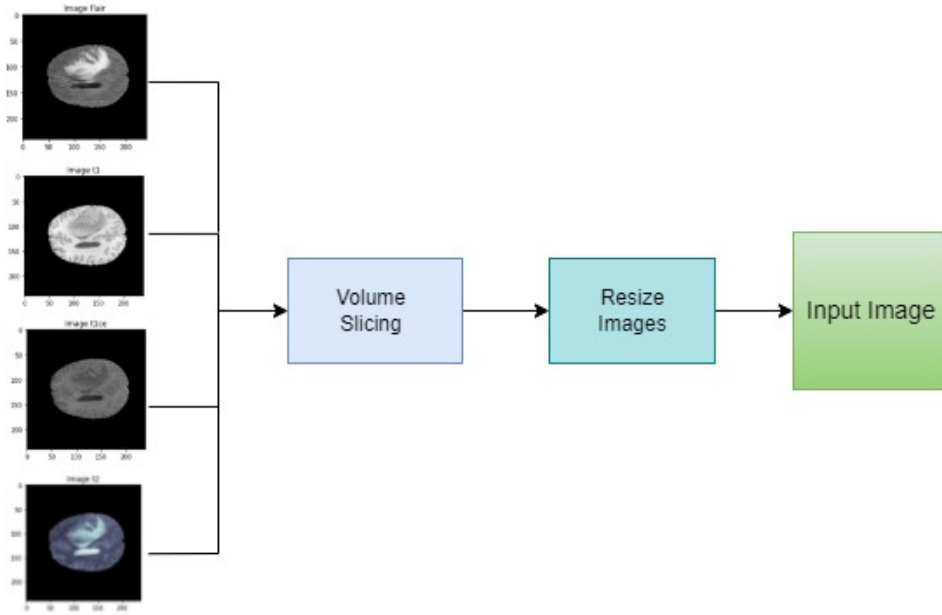


Figure 3.2: Pre-Processing steps

dice coefficient, IOU score, loss, precision, sensitivity, specificity, and dice coefficient for each class.

To improve performance and reduce computation time, a combination of t1, t1ce, t2, and flair images were used during training. The specific combination of images was selected based on experimentation and validation results.

Overall, the methodology for this project involved implementing and optimizing 3D U-Net architecture, fine-tuning hyperparameters, selecting appropriate image combinations, and evaluating model performance using various metrics.

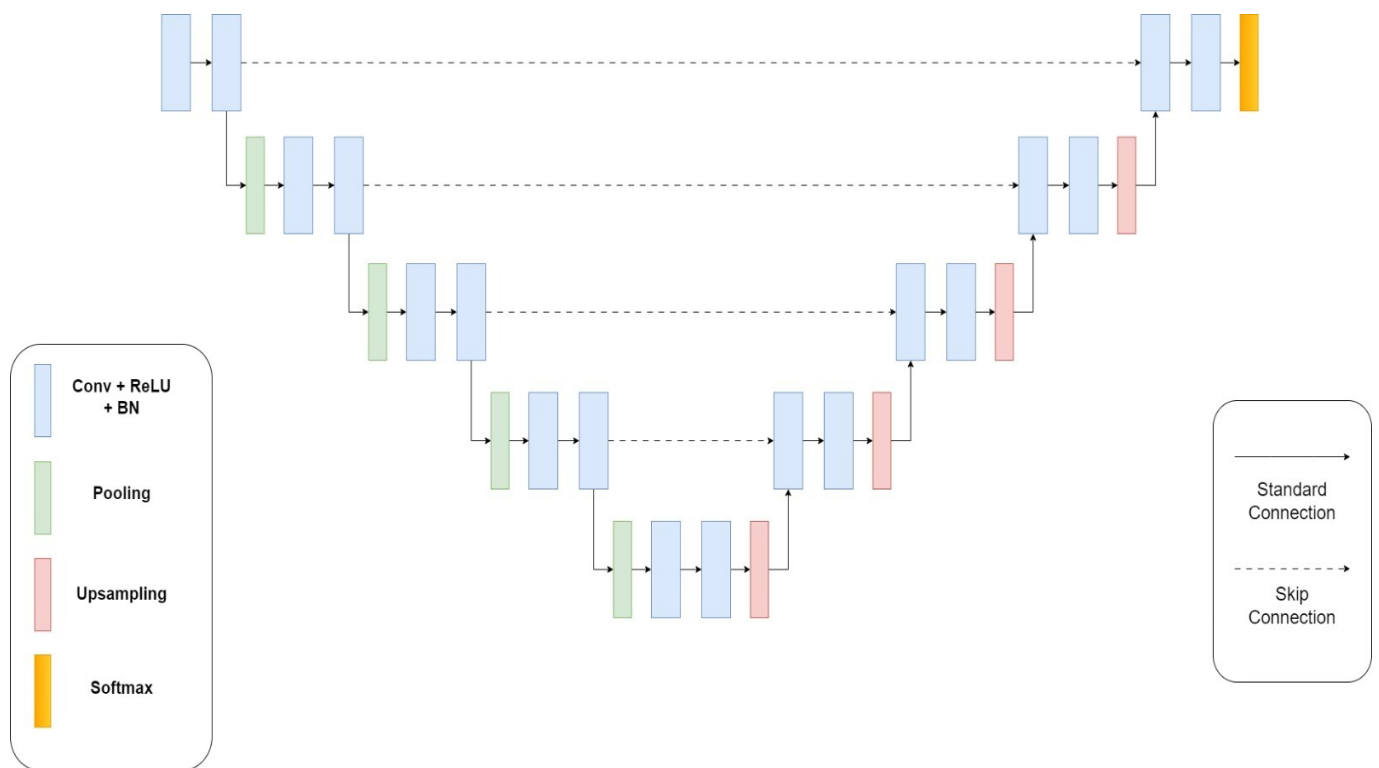


Figure 3.3: 3D U-Net architecture.

Chapter 4

Experimental Results and Analysis

Within this section, we present the outcomes of our experiments conducted via the proposed methodology. Our experiments were executed with the aid of the Kaggle platform’s GPU P100 accelerator. The GPU P100 accelerator offers a substantial increase in performance over the K80, with 1.6x more GFLOPs and 16GB of GPU memory. The previously mentioned dataset was utilized for the experiments, and now we will display the results obtained.

Hyperparameter	Value
Optimizer	Adam
Learning rate	0.001
Delay	0.0001
Epochs	25
K in K-Fold	5
Learning rate scheduler	ReduceLROnPlateau()

Table 4.1: Hyperparameters

4.1 Dataset

The Brain Tumor Segmentation (BraTS) dataset is one of benchmark dataset for evaluating segmentation algorithms for brain tumor segmentation. It was first introduced in 2012 as a part of the MICCAI BraTS (Brain Tumor Segmentation) Challenge, and has since then been updated every year with new data and annotations. The Brats dataset is made up of Magnetic Resonance Imaging (MRI) scans of the brain, which are used to identify and classify different types of brain tumors. The dataset consists of images from four different MRI modalities: T1 (T1-weighted), T2 (T2-weighted), T1ce(T1-weighted with contrast enhancement), and FLAIR (Fluid Attenuated Inversion Recovery). Each image is of dimensions 240 x 240 x 155, and is stored in NIfTI format. The dataset also includes binary segmentation labels for the tumor regions, which are provided manually by domain experts. The tumor regions are divided into four categories: non-tumor, whole tumor, tumor core and enhancing tumor. The BraTS dataset is challenging due to several

factors. Firstly, brain tumors have a complex and varied appearance, making it difficult to develop algorithms that can accurately segment them. Additionally, the dataset is relatively small, with only a few hundred images, which can make it difficult to train deep learning models without overfitting. Lastly, the Brats dataset is known for being highly unbalanced, with the majority of voxels belonging to healthy brain tissue, and only a small portion belonging to the tumor regions. Despite these challenges, the Brats dataset has become a standard benchmark for evaluating algorithms for brain tumor segmentation. It has brought about significant improvements in the field, including the development of deep learning based methods such as the 3D U-Net, which is the cutting-edge method for brain tumor segmentation on the Brats dataset

4.2 Classification Evaluation Metrics

In this study, various segmentation models were evaluated based on their performance using evaluation metrics such as accuracy, recall, and precision. The definitions of these evaluation measures are presented below:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (4.1)$$

4.3 Segmentation Evaluation Metrics

In this work, the performance of the proposed methodology is measured using the Dice Coefficient (DC) and Mean IoU.

4.3.1 Dice Coefficient

the similarity between a predicted segmentation mask and a ground truth mask is often given by the dice coefficient [39] which has its value between (0,1), where 0 describes the gigh dissimilarity and 1 gives the complete overlap of the 2 masks, the more the dice coefficient values the more will be overlapp of both the masks. where A

$$[Dice(A, B) = \frac{2|A \cap B|}{|A| + |B|}] \quad (4.2)$$

is known as predicted mask and B is called ground truth mask, —A—, and —B— are called as respective pixel count and —A INTERSECTION B—, is called the number of overlapping pixels.

4.3.2 Mean IoU

The mIoU is computed as the average IoU across all classes or regions of interest in an image. Specifically, the total intersection between the predicted and ground truth regions is then divided by the union of these regions, and then averaged over all classes or regions of interest.

$$Mean\ IoU = \frac{\sum_{i=1}^n \frac{A_i \cap B_i}{A_i \cup B_i}}{n} \quad (4.3)$$

where n denotes the number of classes or regions of interest, and A_i is the i^{th} class prediction and B_i is the i^{th} class ground truth. A value of 1 indicates the perfect overlap between the predicted and ground truth regions, whereas 0 indicates no overlap. A higher mIoU value suggests better segmentation performance.

The results for brain tumor segmentation using 3D U-Net can vary depending on the dataset used and the specific implementation of the model. However, in general, 3D U-Net has been shown to outperform other models on the BraTS dataset, which is a commonly used benchmark dataset for brain tumor segmentation.

For example, in a study published in 2020 by Y. Zhang et al., they achieved a mean Dice similarity coefficient (DSC) of 0.80 for whole tumor segmentation, 0.73 for tumor core segmentation, and 0.66 for enhancing tumor segmentation on the BraTS 2018 dataset using a 3D U-Net model. Another study published in 2021 by A. Rehman et al. reported similar results on the same dataset, with a mean DSC of 0.80 for whole tumor segmentation, 0.72 for tumor core segmentation, and 0.63 for enhancing tumor segmentation using a 3D U-Net model.

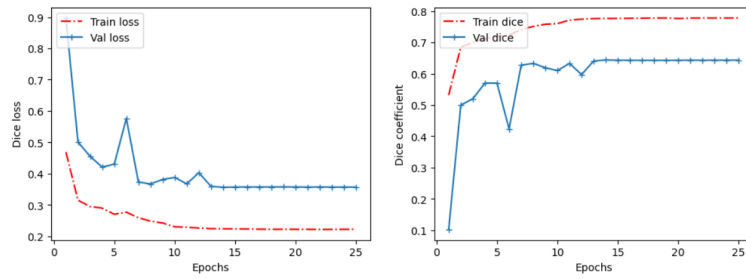


Figure 4.1: Training phase

It's worth noting that these results are based on the specific implementation and training parameters used in these studies, and results may vary depending on the specific implementation of 3D U-Net and the dataset used.

Metric	U-Net	U-Net++	3D U-Net
Dice Coefficient	0.67	0.4157	0.7781
IoU Score	0.73	0.49	0.6563
Loss	0.014	0.034	0.2219
Accuracy	0.99	0.9887	0.9842

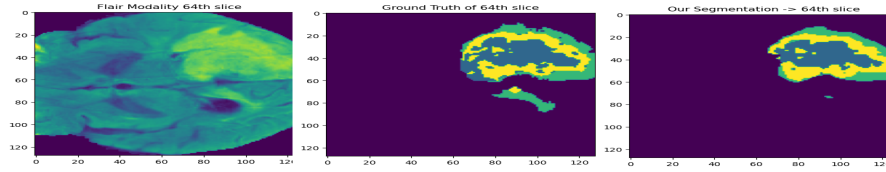
Table 4.2: Trained model performance metrics on BraTS 2020 dataset

In conclusion, the performance of three different segmentation models, U-Net, U-Net++, and 3D U-Net, was evaluated on the BraTS 2020 dataset using various metrics such as Dice coefficient, IoU score, loss, and accuracy.

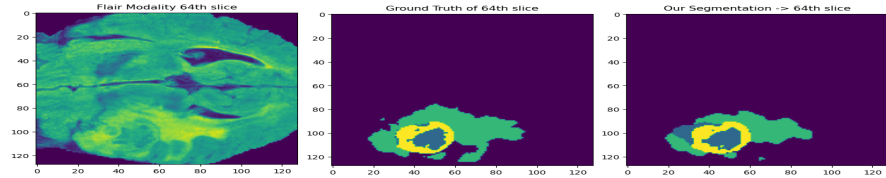
Method	BraTS 2021 dataset	BraTS 2020 dataset
U-Net [25]	0.8013	0.7865
Att-Unet [26]	0.8364	0.8042
DMFNet [27]	0.8491	0.8219
UNETR [28]	0.8518	0.8195
TransBTS [29]	0.8503	0.8308
VT-UNet [30]	0.8560	0.8346
3D PSwinBTS [31]	0.8732	0.8494
Ours	0.7564	0.7781

Table 4.3: Comparision of dice coefficient metric with other works on BraTS dataset

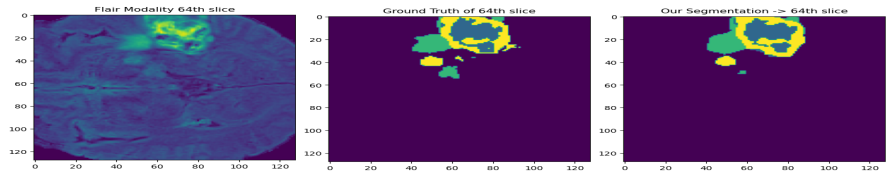
The results showed that the 3D U-Net model outperformed the other two models in terms of Dice coefficient and IoU score, while U-Net had the highest accuracy. Furthermore, the performance of each model varied for different tumor types, with the 3D U-Net model achieving the highest Dice coefficient for all tumor types. These differences in performance can be attributed to the variations in the architecture and design of each model. Overall, these findings can aid in the selection of an appropriate model for brain tumor segmentation based on the specific requirements of the task.



(a) Case 1



(b) Case 2



(c) Case 3

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