Brain Tumor Segmentation Using 3D GAN

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Abstract

Brain tumors are one of the leading cause of death in adults. Tumors are of various shapes and sizes, so accurate segmentation of brain tumor is crucial for diagnosis and treatment planning. Due to complex characters of brain tissue, the proposed method for tumor segmentation is based on 3D U-net neural network which is capable to segment the tumor tissue from normal tissue. 3D U-net architecture is an extension of popular U-net architecture, specially designed for processing three-dimensional volumetric data such as medical imaging scans like MRI. It is widely used in various medical imaging tasks, including segmentation.

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1. Background

According to World Health Organization (WHO), cancerous brain and tumors is the leading cause of death in adults as well as in children. Tumors are the lumps of abnormal tissues. When cells grow old or become damaged, they die, and new cells takes their place. Sometimes this orderly process breaks down and abnormal or damaged cells grow and multiply when they shouldn't. These cells may form tumors, which are lumps of tissues. Tumors can be cancerous or not cancerous (benign). Cancer is caused by changes to DNA. Most cancer-causing DNA changes are occur in sections of DNA called genes. Cancers usually grow faster than benign tumors, spread into surrounding tissues, and cause damage. Cancers can spread to another parts of body in the bloodstream or through the lymph system forming secondary tumors.

A risk factor is anything like age (children, adults), sex (male, female), family history that increases a person's chance of developing a brain tumor. Another risk factor is the exposure to radiation, people who have been exposed to a strong type of radiation have an increased risk of brain tumor. The brain tumors are of various types like Glioma, Ependymal Tumors, Hemangiopericytoma, Pineal Tumors etc. The people who have brain tumor suffers from several symptoms like headache, pressure in head, nausea or vomiting, eye problems like blurry vision, losing sights, trouble with balance, memory problem, confusion, dizziness, hearing problems etc.

The brain tumors are very dangerous because they can put pressure on healthy parts of brain and damage those healthy parts, they can spread in the healthy areas also. Some brain tumors are cancerous or become cancerous. They can block brain fluid flowing though brain and can cause increase in pressure in brain as well as in skull. Depending upon the age of diagnosis, the tumor may cause death. Hence the detection and diagnosis on right time may increase the chance of saving the person's life.

2. Related Works

In past few years, research on segmentation of brain tumors from MRI data has done reasonably. In this section we review some existing methods for brain tumor segmentation, with focus on some deep learning techniques and architectures. Most of the architectures are designed using 3D U-net architecture with some added features or using plain 3D U-net architecture.

The 3D U-net architecture is used (Yan et al., 2023) (Dong et al., 2023) (Ahmad et al., 2020) (Kermi et al., 2022) (Suja et al., 2023) (Győrfi et al., 2023) which consist of two main components one is encoder which extract features from image and the decoder which is responsible for generating segmentation results. Also, pix2pix model is implemented which consist of generator and discriminator, generator tries to generate samples and discriminator tries to distinguish between generated sample and real sample. In order to control generator, modality labels are introduced to the input of generator so that modality of generated image get specified (Institute of Electrical and Electronics Engineers et al., n.d.).

The modified 3D U-net architecture is used, the base model is inspired by U-net and ResNet, the architecture is divided into an encoder-decoder path. The efficient architecture designed with block modifications called BNet blocks. Every stage in encoder path consists of a BNet block instead of residual convolutional block. A BNet block consist of two 3D convolutions including batch normalization and relu followed by skip connection. To reduce features pooling is added between two BNet blocks. Decoder is same as encoder instead of downscaling it uses upscaling (Gammoudi et al., 2023) . Another modified U-net architecture is designed that incorporating additional features and modifications. The architecture consists of two main pathways one is context pathway, and another is localization pathway. The contextual pathway captures the contextual information from 3D image and localization pathway combines contextual information with high resolution features to produce accurate segmentation results (Wicaksana W et al., 2023).

One more modification is done which consist of U-net as base model, to reduce complexity and number of parameters all convolutional operations are replaced with depth wise separable convolutions. This modification will reduce model accuracy slightly hence shuffle mechanism is added which simultaneously applies spatial and channel attention (Magadza and Viriri, 2023).

Another modification is done which is attention U-net architecture with Convolutional Block Attention Module (CBAM) (Baruah et al., 2023). Slight modifications also done in attention-based U-net architecture by adding new block called DWS-Resblock 3D. This block is based on depth wise separable convolution which enables the model to have deeper layers and filters while reducing the number of parameters (Rezaei et al., 2023). The Attention U-net (AUNET) is introduced which follows the U-net architecture except the additional gates are added at each skip connections (Weninger et al., 2021).

The simple 3D CNN architecture also used which consist of multi CNNs with multimodal information fusions which aims to enhance the accuracy of tumor detection by leveraging multimodalities and advanced neural networks (Belinda et al., 2023).

The combination of 3D U-net and transformer also introduced. The 3D U-net is combined with swin transformer, the transformer architecture is initially inspired by the encoder-decoder structure prevalent in RNN distinguishes itself through sophisticated attention mechanism. This mechanism effectively handles sequence to sequence tasks without constraints of sequential data processing (Osei et al., 2023) . Another combination is introduced contains modality specific encoders, multimodal transformers and multimodal shared weight decoders (Ting and Liu, 2023). Autoencoders are also implemented for segmentation of tumors (Pingat et al., 2023).

For data pre-processing some techniques are used like stripping for skull stripping to remove non-brain tissue from images, intensity normalization to normalize pixel intensities of MRI images, patch extraction to handle computational memory, cropping image at center and adding normalization, image registration to align different modalities spatially, intensity clipping and widowing techniques are used to enhance the visibility of specific structure and tissue.

Data augmentation techniques like vertical flip, horizontal flip, rotation, scaling, random gamma distribution are used to avoid overfitting and to get better accuracy on wide variety of data.

3. Aim and Objectives

This study tries to explore the architecture and capabilities of 3D U-net architecture for brain tumor segmentation.

Objectives:

- To explore the accuracy, precision, recall, and overall performance of the 3D U-net architecture compared to existing methods for brain tumor segmentation.
- To explore techniques for optimizing the 3D U-net architecture to improve segmentation and enhance overall performance.
- To compare performance of the simple 3D CNN architecture and the 3D U-net architecture.

4. Significance of Study

- Accurate segmentation of brain tumors is crucial for clinical decision-making, treatment planning, and monitoring of disease progression. By enhancing the accuracy and efficiency of tumor segmentation, the study can contribute to more precise diagnosis and personalized treatment strategies for patients.
- This work tries to implement the 3D U-net architecture and simple 3D CNN architecture for segmentation of brain tumor on a dataset, and to check the performance of the architecture.
- This study also tries to improve the performance of the architecture by trying to modify it.

5. Scope of the Study

The scope of this thesis work is defined as follows:

- Investigating the architecture of the 3D U-net model, including its network design, layers, and parameters. This involves understanding how the model processes 3D medical imaging data for accurate segmentation of brain tumors.
- Selecting appropriate datasets containing 3D brain imaging scans. Also pre-processing the selected data properly.
- Training the architectures on selected dataset using appropriate algorithm and optimize it.
- All the experimentation is done using open source resources.

6. Research Methodology

This work focuses on implementation of 3D U-net architecture and 3D CNN architecture for brain tumor segmentation.

6.1 Dataset Description

The dataset used for this work is BraTS (Brain Tumor Segmentation) 2020 dataset (Kaggle). The dataset contains multimodal Magnetic Resonance Images (MRI). The images are sequentially classified as T1-weighted (T1), T1 contrast enhanced (T1-ce), T2-weighted (T2) and Fluid Attenuated Inversion Recovery (FLAIR). Each of the modality provides different information about the brain tumor characteristics. The labelling of the images has done by expert neurologist manually.

6.2 Data Preprocessing

As the dataset has multimodal images image registration needs to align the different modalities to its consecutive image. Also skull stripping and image cropping needed to focus only on the required part of image i.e. tumor.

6.3 Transformation/Augmentation

To get the better accuracy across wide variety of random contract augmentation technique will be use.

6.4 Models

For this work two model architectures are going to implement.

1. 3D U-net model
2. Simple 3D CNN model

The 3D U-net architecture is based on the U-net architecture, it is designed to process the volumetric data such as 3D brain tumor images. The architecture consist of encoder-decoder structure with skip connections corresponding to encoder layer and decoder layer to facilitate the feature propagation and preserver the spatial information.

The simple 3D CNN (Convolutional Neural Network) is specially designed to process the 3D volumetric data such as 3D MRI data. Unlike the 2D CNN which are operated on 2D images which contains only height and width, 3D CNN are capable to process spatial information along with depth dimension as well.

6.5 Implementation

In order to 3D U-net architecture, initial focus is lies on encoder and decoder implementation. The work of encoder is to downscale the image, it contains CNN layers which are responsible to extract features from image and pooling layers are responsible to reduce the dimensionality of extracted features. In this study 3D CNN layers with (3, 3, 3) size kernel and relu (Rectifier Linear Unit) activation function are implemented. For pooing layer (2, 2, 2) size pool is implement. The construction of encoder is progress until the bottleneck layer which is 1D vector, 3D batch normalization layer is added in between each CNN layer.

Similarly to implement decoder which is responsible to upscale image, transposed convolutional layers with relu activation and (3, 3, 3) kernel size is used. In between each consecutive encoder-decoder layer skip connections are added which are nothing but concatenating the feature maps of consecutive encoder-decoder to preserve the spatial information. The graphical representation of 3D U-net architecture is given in figure 6.5.1.

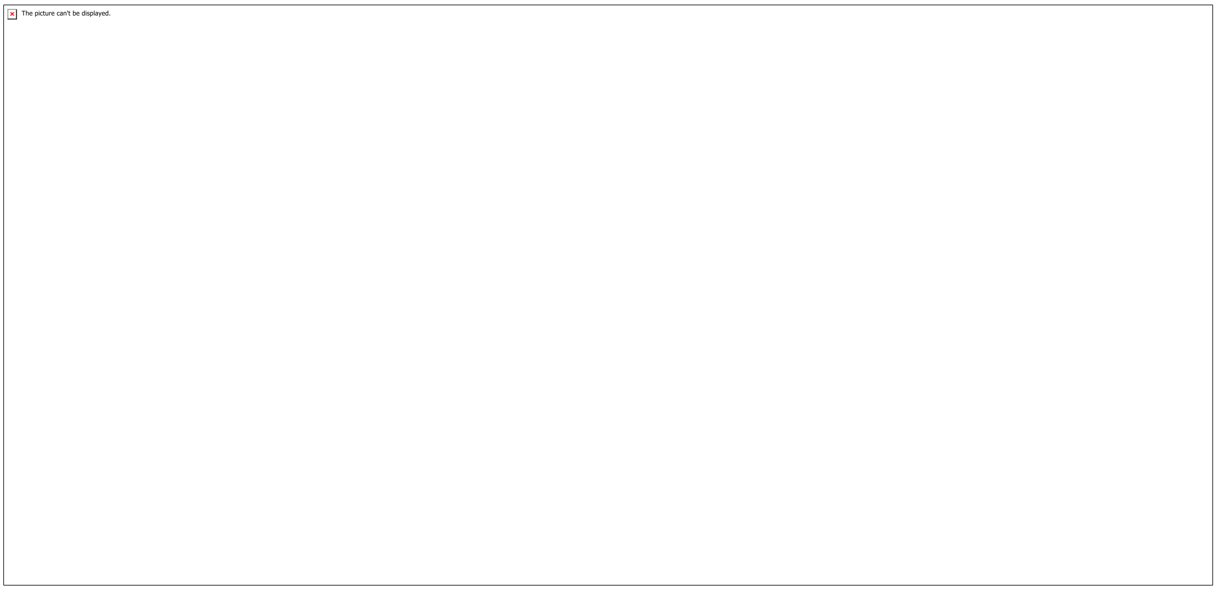


Figure 6.5.1 U-Net Architecture

In order to implement the 3D CNN model multi-CNNs with multimodal information fusion is used. This model consist of 3D CNN layers with (3, 3, 3) size kernel and relu activation function. In order to reduce the feature maps (2, 2, 2) size pooling is used, also after each CNN layer 3D batch normalization is provided. Sotmax activation function is used in last dense layer. The graphical representation of 3D CNN model is given in figure 6.5.2

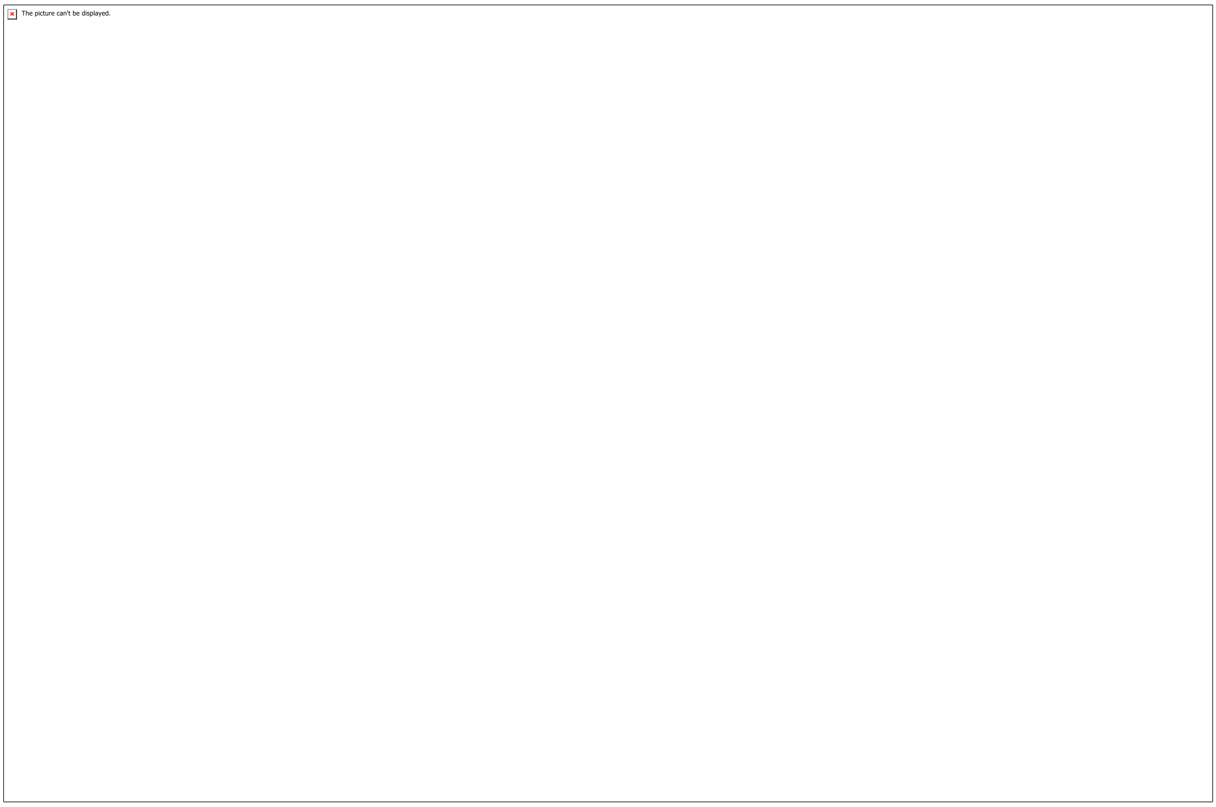


Figure 6.5.2 3D CNN

7.6 Evaluation

The evaluation of segmentation is done by following metrics

1. Accuracy: Accuracy measures the correctness of segmentation results.
2. Precision: Precision measures the proportion of actual positive results among the all positive predicted results.
3. Recall: Precision measures the proportion of actual positive results among the all ground truth positive.

7. Required Resources

7.1 Hardware Requirement

- A laptop/desktop with access to GPU to train deep learning models.

7.2 Software Requirement

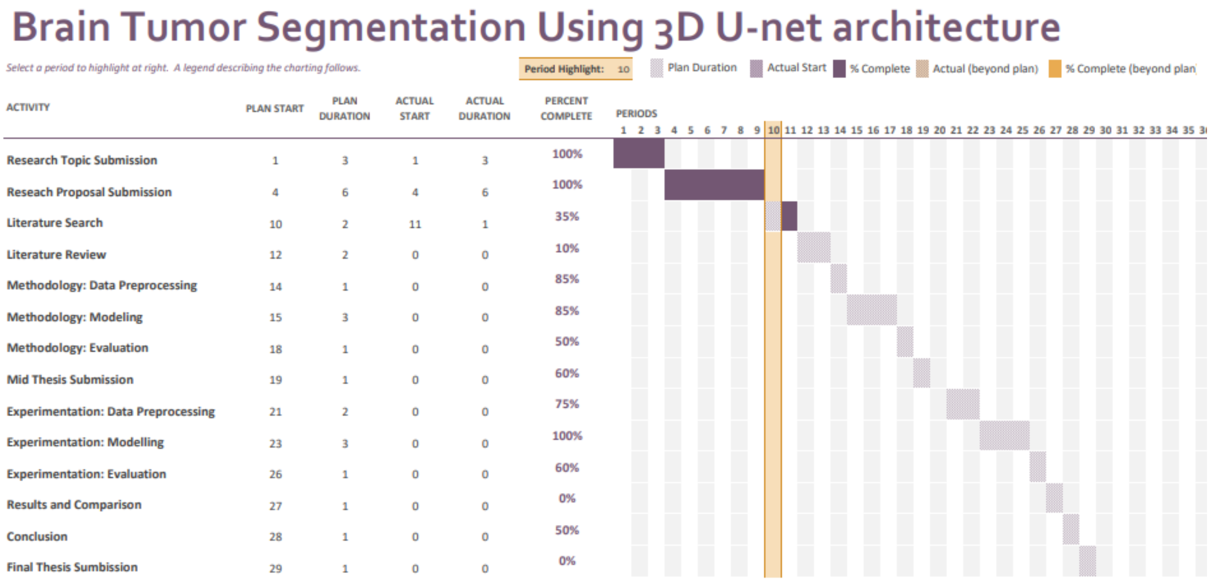
- Python: For coding.
- Deep learning Libraries: Keras, Kensorflow
- Web Browser
- Other Libraries: OpenCV, Numpy etc

7.3 Dataset Requirement

- BraTS 2020 dataset

8. Research Plan

8.1 Gant Chart



Brain Tumor Segmentation Using 3D U-net architecture

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Period Highlight: 10

Plan Duration | Actual Start | % Complete | Actual (beyond plan) | % Complete (beyond plan)

ACTIVITY	PLAN START	PLAN DURATION	ACTUAL START	ACTUAL DURATION	PERCENT COMPLETE
Research Topic Submission	1	3	1	3	100%
Reseach Proposal Submission	4	6	4	6	100%
Literature Search	10	2	11	1	35%
Literature Review	12	2	0	0	10%
Methodology: Data Preprocessing	14	1	0	0	85%
Methodology: Modeling	15	3	0	0	85%
Methodology: Evaluation	18	1	0	0	50%
Mid Thesis Submission	19	1	0	0	60%
Experimentation: Data Preprocessing	21	2	0	0	75%
Experimentation: Modelling	23	3	0	0	100%
Experimentation: Evaluation	26	1	0	0	60%
Results and Comparison	27	1	0	0	0%
Conclusion	28	1	0	0	50%
Final Thesis Sumbission	29	1	0	0	0%

Figure 8.1.1 Gant Chart

1 Period = 1 Week

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