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Internship Report

Brain Tumor Segmentation in Multimodal MRI

Summer Research Internship
(July - September 2023)
under
Dr. Umarani Jayaraman (Faculty of CSE at IIITDM Kancheepuram)

1 Summary of Internship

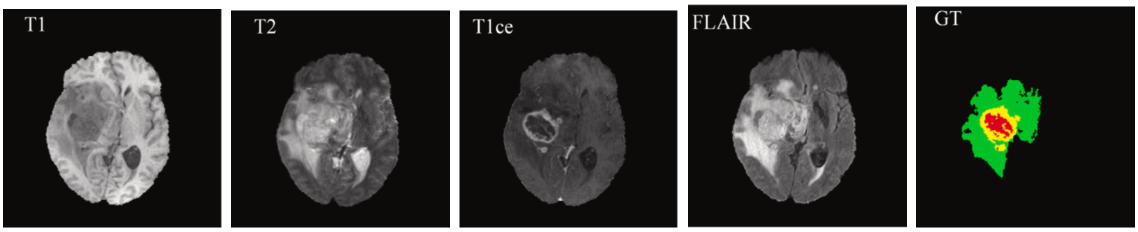
1.1 Introduction

Brain tumor segmentation in multimodal MRI [1, 2, 3] involves the application of advanced image analysis techniques to segment and delineate tumor regions within brain images that are acquired using multiple MRI (magnetic resonance imaging) modalities. Multimodal MRI combines information from different MRI sequences or modalities to provide a more comprehensive view of the brain's internal structures, including any abnormal growths like tumors, while traditional MRI only captures a single type of image. This approach enhances the accuracy of tumor segmentation by utilizing complementary information from different image types.

The common MRI modalities used for multimodal brain tumor segmentation [4, 5, 6] include :

- **T1-weighted Imaging (T1) :** This modality provides information about the brain's anatomy and morphology. T1-weighted images are commonly used for visualizing the brain's overall structure and tissue contrast.
- **T2-weighted Imaging (T2) :** T2-weighted images highlight differences in tissue characteristics, particularly fluids. They help in identifying edema and other abnormalities.
- **T1 Contrast-Enhanced Imaging (T1CE) :** In this modality, a contrast agent is administered to the patient before the MRI scan. This enhances the visibility of blood-brain barrier disruption and areas of increased vascularity, often associated with tumor growth.
- **T2 Fluid Attenuated Inversion Recovery (FLAIR) :** FLAIR images are sensitive to fluid accumulation, making them useful for detecting edema, which is common around tumors.
- **Ground Truth or Segmentation Mask (GT/Mask)** : These are manually annotated or labeled data that serve as a reference for training and evaluating segmentation algorithms. It involves human experts carefully outlining the tumor regions on the MRI images. The ground truth provides the correct segmentation boundaries that algorithms should aim to replicate during the segmentation process.

All the MRI Modalities and the Ground Truth (GT/Mask) mentioned above are shown in Figure 1.



(a) T1 (b) T2 (c) T1CE (d) FLAIR (e) GT/Mask

Figure 1: Modalities in Multimodal MRI (T1, T2, T1CE and FLAIR) [(a) to (d)] and Ground Truth(e). The ground truth (GT) segmentation label provided by domain experts (the green, yellow and red represent edema (ED), enhancing tumor (ET), and necrosis and non-enhancing tumor (NCR/NET), respectively)

1.2 Motivation

Brain Tumors, especially the cancerous tumors are highly dangerous and life threatening, killing thousand of people every year. Thus, there is a need for continuous advancement and research for the diagnosis and treatment of this disease. The reasons and motivation to work on this Research Topic (Brain Tumor Segmentation in Multimodal MRI [1]) are as follows:

- Accurate and Rapid Diagnosis of the disease which helps in Treatment Planning of the disease.
- Advancing Neurosurgical Techniques to enhance the precision and safety of surgical procedures.
- Reducing Human Effort and Bias & Time-Efficient Diagnosis by automating the process of Brain Tumor Segmentation.
- Early Detection and Intervention : Early detection and intervention of brain tumors is critical for successful treatment.
- Research and Innovation: Research in this domain is leading to continuous development and refining of segmentation algorithms, leading to advancements in medical imaging and artificial intelligence.

1.3 Scope

The scope of the Internship are as follows :

- Understanding the Research Problem (Brain Tumor Segmentation in Multimodal MRI [1]), the Benchmark Dataset for the Research Problem (BraTS2018, BraTS2019, BraTS2020) [4, 5, 6] and the various objectives associated with the Research Problem [2].

1.4 Objectives

The objectives of the Internship are as follows :

- Detailed Literature Survey on the Research Topic to have a comprehensive understanding of the various advancements in this Research Area and to have a detailed knowledge of the various latest state-of-the-art Solutions/Models and their performance metrics.
- Study in detail the latest research paper with highly accurate state-of-the-art model/solution and understand the working and various scope of the model
- Implementation of one of the latest state-of-the-art paper/solution. [7]

2 Contribution

2.1 Comprehensive Literature Survey

The Research Topic is a well-distinguished topic of interest for research for over a decade. There are various Research & Review papers written on this topic. Below are the Review and Research papers with latest state-of-the-art solutions/models that we studied under this Internship :

2.1.1 Review Papers

- A review on brain tumor segmentation of MRI images [2]
- Brain tumor segmentation of MRI images: A comprehensive review on the application of artificial intelligence tools [1]
- Vision transformers in multi-modal brain tumor MRI segmentation: A review [3]

2.1.2 The Benchmark Dataset BraTS (2018-20)

The BraTS (Brain Tumor Segmentation) dataset is a collection of multimodal MRI scans along with corresponding manual tumor segmentations. It is used for the annual BraTS challenge, which aims to promote the development of accurate algorithms for brain tumor segmentation and other related tasks. The dataset is an invaluable resource for researchers and data scientists working in the field of medical image analysis and neuroimaging.

Here are the details about the BraTS datasets [4, 5, 6] for 2018, 2019, and 2020, including the number of cases and the dimensions of each modality:

1. **BraTS2018 [4]:**

- Number of Cases: 285
- Modalities & Dimensions : T1, T1CE, T2 and FLAIR - all 3D MRI Volume. Each modality has dimensions (Height x Width x Depth), usually around 240 x 240 x variable depth, depending on the specific scan.

2. **BraTS2019 [5]:**

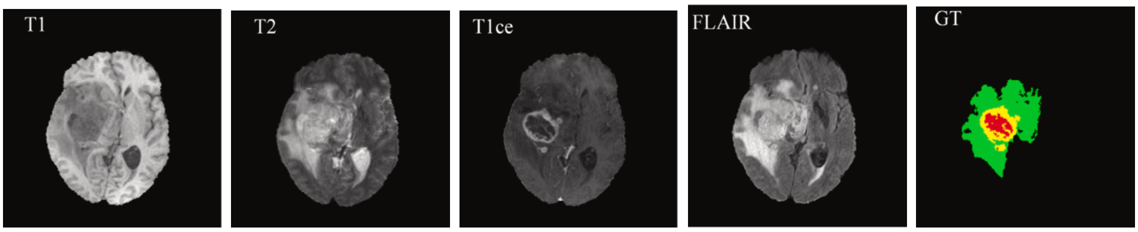
- Number of Cases: 335
- Modalities & Dimensions : Same as BraTS2018. Dimensions are similar to BraTS2018, with 3D volumes for each modality.

3. **BraTS2020 [6] :**

- Number of Cases: 369
- Modalities & Dimensions: Same as BraTS2018 and BraTS2019. Dimensions are similar to previous years, with 3D volumes for each modality.

The dataset is added, deleted or replaced in each year's competition to upgrade its scale. BraTS2018, 2019, and 2020 have 285, 335, and 369 annotated brain tumor samples for model training, respectively.

The labels contain four classes: background, NCR/NET, ED and ET. The evaluation is based on three different brain tumor regions: **Whole Tumor** (**WT** = NCR/NET + ED + ET), **Tumor Core** (**TC** = NCR/NET + ET) and **Enhancing Tumor** (**ET**). The contents of BraTS Dataset are shown in Figure 2.



(a) T1 (b) T2 (c) T1CE (d) FLAIR (e) GT/Mask

Figure 2: Modalities in Multimodal MRI (T1, T2, T1CE and FLAIR) [(a) to (d)] and Ground Truth(e).he ground truth (GT) segmentation label provided by domain experts (the green, yellow and red represent edema (ED), enhancing tumor (ET), and necrosis and non-enhancing tumor (NCR/NET), respectively)

2.1.3 Latest Research Papers with the state-of-the-art solutions/models

- **Myronenko (Autoencoder Regularization) :** Proposed semantic segmentation network with an encoder-decoder architecture, incorporating a variational auto-encoder to work on limited training dataset size.[8]
- **N3D (3D UNet) :** Proposed a 3D U-Net for brain tumor segmentation and prediction of survival days. [9]
- **HNF-Net :** Proposed a 3D High-resolution and Non-local Feature Network (HNF-Net) is introduced for accurate brain glioma segmentation from multi-parametric MR images. This network also incorporates a parallel multi-scale fusion (PMF) module and an Expectation-Maximization Attention (EMA) module to enhance high-resolution feature representation and capture long-range contextual information efficiently. [10]
- **CENET :** CE-Net is a 2D medical image segmentation framework with feature encoder, context extractor, and feature decoder components. It leverages pretrained ResNet blocks, along with dense atrous convolution (DAC) and residual multi-kernel pooling (RMP) blocks, to capture high-level information and spatial details effectively. [11]
- **NoNewNet :** Improvised U-Net with minor modifications and focused on training process in better way by incorporating region based training, additional training data and a simple postprocessing technique. Thus, making simple U-Net more powerful. [12]
- **U-Net++ :** A neural architecture designed for both semantic and instance segmentation. It addresses limitations by utilizing an ensemble of U-Nets with varying depths, facilitating co-learning through deep supervision. Redesigned skip connections contribute to enhanced feature fusion by aggregating diverse semantic scale features. Additionally, a devised pruning scheme is implemented to accelerate the inference speed of the UNet++ model [13]
- **Point-UNet :** Point-Unet, an innovative approach merging deep learning and 3D point clouds for volumetric segmentation. The method employs an attentional probability map to predict regions of interest within the volume. It then samples the volume into a sparse point cloud, which is segmented using a point-based neural network, effectively combining efficiency and accuracy in segmentation. [14]
- **RFNet :** Proposed a model - RFNet, which employs a Region-aware Fusion Module (RFM) for effective multi-modal brain tumor segmentation. RFM adaptsively fuses modal features based on varying regions of sensitivity. The approach addresses incomplete multi-modal data with a segmentation-based regularizer, enhancing training. By segmenting each modality individually and fused features collectively. It improves the representation ability of the final fused features. [15]
- **TransUnet :** TransUNet, a robust method for medical image segmentation that combines Transformers and U-Net. The Transformer encodes image patches from a CNN feature map to capture global context, while the decoder upsamples the encoded features for precise localization. By integrating both techniques, TransUNet offers a powerful approach to enhance medical image segmentation. [16]
- **TransBTS :** The paper introduces TransBTS, a pioneering approach that combines Transformers and 3D CNN for MRI Brain Tumor Segmentation. TransBTS employs an encoder-decoder structure: the encoder uses 3D CNN to extract spatial feature maps, which are transformed into tokens for global feature modeling in the Transformer. The decoder utilizes Transformer-embedded features and progressive upsampling to predict detailed segmentation maps, effectively integrating local and global context information. [17]
- **SwinTrans (with SPD + ED + MFIB) :** Proposed a method that fuses deep semantics and edge information from multimodal MRI for improved accuracy. It comprises a semantic segmentation module using Swin Transformer, an edge detection module with a novel edge spatial attention block (ESAB), and a

feature fusion module employing a multi-feature inference block (MFIB) for effective reasoning and information dissemination. The proposed approach enhances multimodal information utilization and segmentation precision[18]

The above paper [**SwinTrans (with SPD + ED + MFIB)** [18]] is so far the best paper in terms of segmentation accuracy (Dice Score and Hausdorff Distance) and the ability to get trained on a small sized dataset (high locality induction bias). Hence, we used the idea behind this paper/model for our research and implementation work.

2.1.4 Comparative Study of the Models listed above

Table 1 to 3 shows the Comparative Study of the Evaluation Metrics (Dice Score and Hausdorff Distance) of the various models listed in the above section. The evaluation metrics are calculated for the BraTS2018, BraTS2019 and BraTS2020 Benchmark Datasets.

Table 1: Objective evaluation results of models on the BraTS2018 Benchmark

Model	**Paper Title**	**Reference**	**Dice Score**	**Hausdorff Distance**
UNet++	Unet++: Redesigning skip connections to exploit multiscale features in image segmentation	[13]	84.36	6.049
CENET	Ce-net: Context encoder network for 2d medical image segmentation	[11]	84.60	6.193
NoNewNet	No new-net	[12]	84.90	5.357
Myronenko	3d mri brain tumor segmentation using autoencoder regularization	[8]	85.90	5.500
TransUnet	Transunet: Transformers make strong encoders for medical image segmentation	[16]	85.95	4.553
Point-Unet	Point-unet: A context-aware point-based neural network for volumetric segmentation	[14]	86.13	6.010
SwinTrans (SF+EF)	**Brain tumor segmentation based on the fusion of deep semantics and edge information in multimodal mri**	[18]	**86.93**	**4.193**

Table 2: Objective evaluation results of models on the BraTS2019 Benchmark

Model	**Paper Title**	**Reference**	**Dice Score**	**Hausdorff Distance**
TransBTS	Transbts: Multimodal brain tumor segmentation using transformer	[17]	83.62	5.143
UNet++	Unet++: Redesigning skip connections to exploit multiscale features in image segmentation	[13]	85.68	5.060
HNF-Net	Learning high-resolution and efficient non-local features for brain glioma segmentation in mr images	[10]	86.16	4.292
N3D	3d u-net based brain tumor segmentation and survival days prediction	[9]	85.90	5.500
TransUnet	ransunet: Transformers make strong encoders for medical image segmentation	[16]	85.95	4.553
Point-Unet	Point-unet: A context-aware point-based neural network for volumetric segmentation	[14]	86.13	6.010
SwinTrans (SF+EF)	**Brain tumor segmentation based on the fusion of deep semantics and edge information in multimodal mri**	[18]	**86.93**	**4.193**

Table 3: Objective evaluation results of models on the BraTS2020 Benchmark

Model	**Paper Title**	**Reference**	**Dice Score**	**Hausdorff Distance**
Point-Unet	Point-unet: A context-aware point-based neural network for volumetric segmentation	[14]	83.02	8.260
TransBTS	Transbts: Multimodal brain tumor segmentation using transformer	[17]	83.52	10.893
RFNet	Rfnet: Region-aware fusion network for incomplete multi-modal brain tumor segmentation	[15]	84.77	-
U-Net++	Unet++: Redesigning skip connections to exploit multiscale features in image segmentation	[13]	85.06	5.370
SwinTrans (SF+EF)	**Brain tumor segmentation based on the fusion of deep semantics and edge information in multimodal mri**	[18]	**87.95**	**4.585**

2.2 Implemented Model/Solution

Paper : Brain tumor segmentation based on the fusion of deep semantics and edge information in Multimodal MRI [18] — Z. Zhu, X. He, G. Qi, Y. Li, B. Cong, and Y. Liu, "Brain tumor segmentation based on the fusion of deep semantics and edge information in multimodal mri," Information Fusion, vol. 91, pp. 376–387, 2023 Paper Link

2.2.1 Model Architecture in Detail

The Model consists of three main Modules - a semantic segmentation module, an edge detection module and a feature fusion module. The architecture of the model is shown in the Figure 3 below.

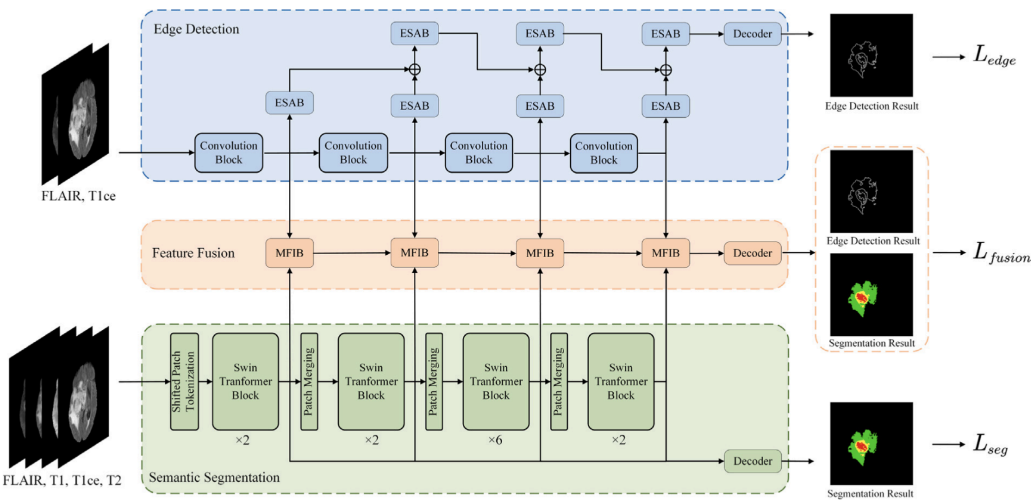


Figure 3: The framework of the proposed brain tumor segmentation model. It mainly consists of three modules - a semantic segmentation module, an edge detection module and a feature fusion module (Reference : [18])

The **Semantic Segmentation Module** consists of a Swin Transformer to extract the deep semantic features from multimodal MRI scans including FLAIR, T1, T1ce and T2. It employs a **Shifted Patch Tokenization (SPD)** strategy that helps the transformer to train on a small dataset (high locality induction bias). The architecture of Semantic Segmentation Module is shown in Figure 4.

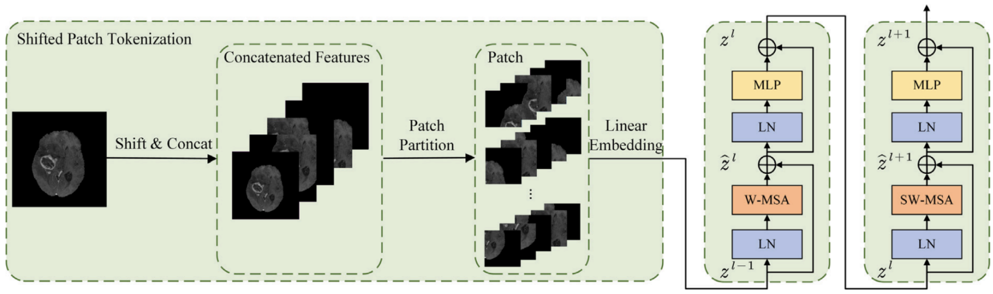


Figure 4: Semantic Segmentation Module consisting of Swin Transformer with Shifted Patch Tokenization (SPD) Strategy (Reference : [18])

The **Edge Detection Module** consists of convolutional network as the base model and is used in designing **Edge Spatial Attention Blocks (ESABs)** for feature enhancement. FLAIR and T1ce are selected as the input of the edge detection module, considering the modal characteristics of these MRI modalities. The architecture of Edge Detection Module is shown in Figure 5.

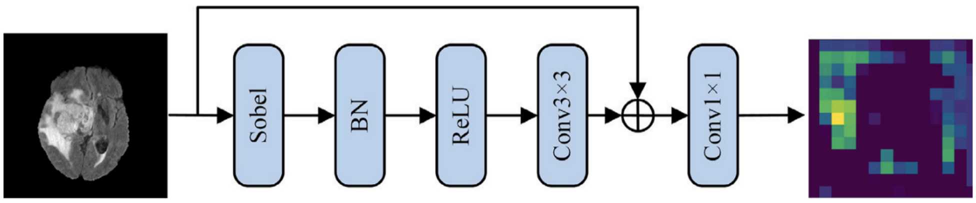


Figure 5: Edge Spatial Attention Blocks (ESABs) designed for edge feature enhancement (Ref : [18])

The **Feature Fusion Module** (shown in Figure 6) consists of several **Multi-Feature Inference Blocks (MFIBs)** which involves **Graph Convolution** [19, 20], shown in Figure 7, aiming to fuse the semantic features and the edge features obtained at multiple levels from the semantic segmentation module and the edge module, respectively.

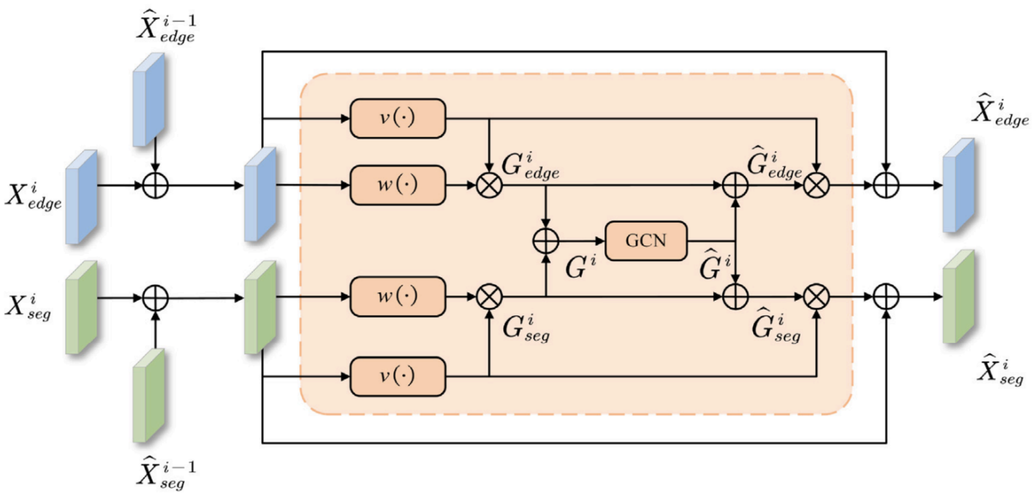


Figure 6: The complete architecture of ith Multi-Feature Inference Block (MFIB) in Feature Fusion Module (Ref : [18])

To reconstruct the segmentation result, a successive expanding decoder that is widely adopted in the **U-Net** [21] - like architectures is used. The Semantic Segmenation and the Edge Detection Modules are trained first, then, the output of the feature fusion module is used to supervise the training of the entire model.

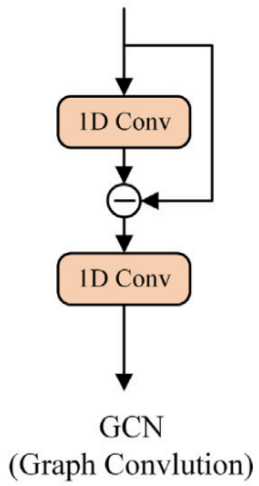


Figure 7: The architecture of Graph Convolution Network (GCN) MFIB (Ref : [18])

2.2.2 Results obtained in the Research Paper

As per the research paper, following are the Objective Evaluation Results (**Dice Score** and **%95 Hausdorff Distance**) for the three tumor regions : **Whole Tumor (WT = NCR/NET + ED + ET)**, **Tumor Core (TC = NCR/NET + ET)** and **Enhancing Tumor (ET)**. The evaluations are done on **BraTS2018**, **BraTS2019** and **BraTS2020** Datasets [4, 5, 6].

Table 4: Objective evaluation results of the Research Paper Model [18] on the BraTS2018 Benchmark

	WT	**TC**	**ET**	**Average Score**
Dice Score	90.89	87.96	81.94	86.93
Hausdorff Distance	3.923	5.217	3.440	4.193

Table 5: Objective evaluation results of the Research Paper Model [18] on the BraTS2019 Benchmark

	WT	**TC**	**ET**	**Average Score**
Dice Score	91.58	89.24	83.84	88.22
Hausdorff Distance	3.866	5.118	3.080	4.021

Table 6: Objective evaluation results of the Research Paper Model [18] on the BraTS2020 Benchmark

	WT	**TC**	**ET**	**Average Score**
Dice Score	91.03	88.22	84.61	87.95
Hausdorff Distance	4.719	5.985	3.051	4.585

2.2.3 Implementation of the Model and Results

Github repository: Brain Tumor Segemntation in Multimodal MRI - using Information Fusion of Semantic and Edge Features (Swin Transformer + SPD + ESAB + NFIB) - Implementation by Saurabh Gupta [7]

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3 Conclusions

3.1 About the Learning Experience

In this **Summer Research Internship (June-August 2023) under respected Dr. Umarani Jayaraman (Faculty of CSE at IIITDM Kancheepuram)** on the Topic - **Brain tumor segmentation in multimodal MRI**, I got a wonderful opportuninty to learn and work on the latest state-of-the-art research works, models and solutions.

As part of this internship, not only I came to know about the various models used for Medical Image Segmentation but also their working and underlying mathematical intuition used as the backbone of these models. Thus, in future it will help me to use the motivation and mechanism behind these models, in this research topic as well as other Image Segmentation problems in this field.

The implementation of the latest best state-of-the-art solution given in the Paper : Brain tumor segmentation based on the fusion of deep semantics and edge information in Multimodal MRI [18], I learnt how to implement custom Deep Learning (DL) Models (Swin Transformer + ESAB + MFIB with GCN) from scratch using PyTorch and Einops along with the fundamental python Data Science (DS) and Machine Learning (ML) Modules like Numpy, Pandas and Matplotlib. This, was one of my best experience in the Internship as I learnt about how to implement any advanced, custom ML/DL models from scratch which will help me in building and testing new models for this Research Topic in future.

3.2 Future Ideas and Work

Following ideas can be explored and experimented in the future :

- Similar to the Information Fusion of the Semantic and Edge Features in the Research Paper [18], the contrast information of the Tumor can also be used for fusion, especially the Tumor Core Region (clearly visible from the visual inspection of the T1CE and FLAIR modalities).
- Ensembling of multiple state-of-the-art models can be done to increase accuracy.

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