BRAIN TUMOR SEGMENTATION

ARDHRA M A(JEC20AD015)
MADHAV M(JEC20AD028)
RAHUL SREENIVASAN P(JEC20AD041)
SULEKHA P S(JEC20AD051)

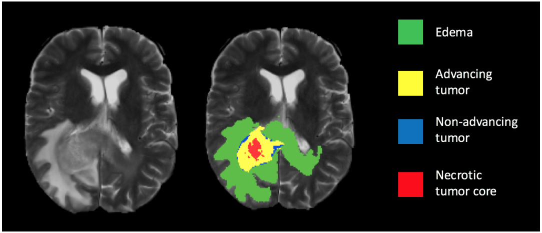
Supervised by: Mr.SHINE P XAVIER

Department of Artificial Intelligence and Data Science,
Jyothi Engineering College, Cheruthuruthy.

November 25, 2024

Introduction

- This project focuses on automating brain image segmentation from MRI scans.
- Advanced deep learning techniques are employed to extract features and identify brain structures.
- The project aims to revolutionize neuroimaging, offering faster and more accurate diagnoses.



Literature Survey

- 3D Brain tumor segmentation
  - 3D UNet
    - 3D Convolutional Neural Network for Brain Tumor Segmentation
    - Brain Tumor Segmentation with Self-Ensembled, Deeply-Supervised 3D U-Net Neural Network
    - Attention 3D U-Net with Multiple Skip Connections for Segmentation of Brain Tumor Images
    - Context-Aware 3D UNet for Brain Tumor Segmentation
    - Brain Tumor Segmentation Based on 3D UNET with Multi-Class Focal Loss
    - Brain tumor segmentation with self-ensembled,deeply-supervised 3d u-net neural networks: A brats2020 challenge solution
    - A stackedmulti-connection simple reducing net for brain tumor segmentation
  - CNN
    - MRI-based Brain Tumor Image Detection Using CNN-based Deep Learning Method
    - A 3D Fully Convolutional Neural Network with Atrous-Convolution Feature Pyramid for Brain Tumor Segmentation via MRI Images
    - Brain Tumor Volumetric Segmentation in Multimodal MRI Using 3D Convolutional Neural Networks
    - 3D Automatic Segmentation of Brain Tumor Based on Deep Neural Network and Multimodal MRI Images
  - SVM
    - Brain tumor segmentation and classification by improved binomial thresholding and multi-features selection
    - Brain MRI tumor segmentation with 3D intracranial structure deformation feature
    - An automated MRI brain image segmentation and tumor detection using som-clustering and proximal support vector machine classifier
  - OTHERS
    - Fuzzy classification
      - 3D brain tumor segmentation in MRI using fuzzy classification, symmetry analysis and spatially constrained deformable models
    - Logistic Regression
      - 3D variational brain tumor segmentation using a high dimensional feature set

3D UNet

- The proposed paper [1] employs multi-class focal loss to address class imbalance,enhancing the model's performance.
- Paper [2] distinguishes itself by introducing attention modules and multiple skip connections , enabling more effective feature selection and spatial awareness.
- Standardizing input data with MRI intensity normalization and z-score normalization improves the model's ability to learn from consistent image intensities is done in this paper[3].
- The model in [4] takes a unique approach by integrating the Two-Stage Optimal Mass Transport algorithm for efficient brain image representation.

Literature Survey

1. The paper [5] focuses on improving computational efficiency by simplifying the network structure, reducing parameters, and emphasizing the effectiveness of cascade networks.
2. The model in [6] stands out by incorporating self-ensembling and deep supervision techniques within the 3D U-Net architecture, which contributes to improved segmentation accuracy and network training.
3. This [7] utilizes 3D ConvNet with UNet for efficient and accurate 3D MRI brain tumor segmentation, achieving a Dice score of 0.71, despite memory challenges and limited interpretability.

Literature Survey

CNN

- The approach in [8] focuses on brain tumor segmentation from multimodal MRI images, with additional preprocessing steps to improve image quality.
- Utilizing a nine-layer CNN in paper [9], this model achieves a remarkable 99.74% accuracy in brain tumor detection.
- The model in [10] focuses on effective segmentation of tumor substructures using an atrous-convolution feature pyramid and a three-hierarchy pyramidal structure.
- This model in [11], inspired by variational autoencoders and skip connections, offers improved performance in brain tumor volumetric segmentation, along with data augmentation.

SVM

- This paper [12] focuses on using improved binomial thresholding for segmentation and features like geometric and Harlick texture features for classification.
- This paper [13] introduces a unique approach that uses the deformation features extracted from lateral ventricles in brain images segmentation and classification.
- The paper [14] presents the FAHS-SVM method, encompassing pre-processing, feature extraction, SVM classification for brain tumor detection and segmentation, with features such as mean intensity, homogeneity, direction moment, and more.

OTHERS

- This [15] hybrid method employs symmetry analysis, fuzzy classification, and deformable models for brain tumor detection, integrating deformable models and spatial relations with preprocessing steps.
- Employs a Logistic Regression-based conditional model in [16] with robust preprocessing for variational brain tumor segmentation using high-dimensional features and alignment-based models.

Comparison

Rank	Model	Summary Of Advantages	Summary Of Disadvantages
1	3D U-Net	High accuracy, effective 3D utilization, versatility.	High computational and memory requirements.
2	CNN	High accuracy, automatic feature learning.	Computational complexity, limited interpretability.
3	Logistic regression	High accuracy, comprehensive preprocessing.	Trains a set of U-Nets as generators and fully convolutional networks as discriminators.
4	SVM	Effective for non-linear data, strong generalization.	Moderate performance in accuracy, sensitivity to outliers.
5	fuzzy classification	Automation, applicability, robustness.	Limited generalizability .

Table 1: Advantages and Disadvantages

Gaps Identified

1. Generalizability and Real-World applicability.
2. Data augmentation and Regularization.
3. Robustness to noise.
4. Optimization and Efficiency.

Problem Statement

This project focus to satisfy the need for a highly precise and efficient automated 3D brain tumor segmentation solution from MRI scans, as current manual and automated methods often fall short in delivering the necessary level of accuracy.

Objectivies

- Locate and identify the regions in the brain that contain tumors.
- Perform multi-class segmentation by classifying different tumor components.
- Achieve high accuracy in the segmentation of brain tumors.
- Develop an efficient model that can handle 3D medical image data while keeping computational resources in mind.
- Implement data augmentation techniques to improve model performance

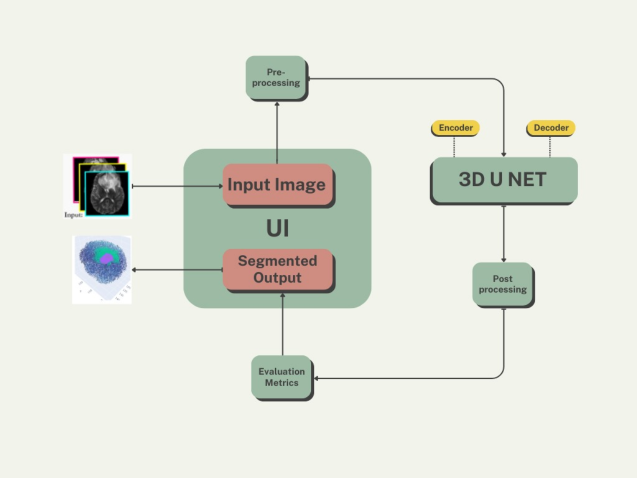


Figure 1: System Architecture

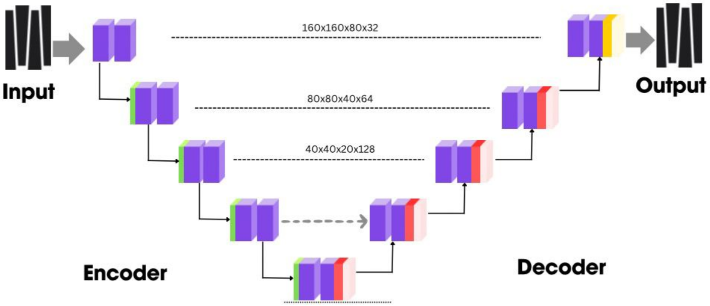


Figure 2: Network Architecture

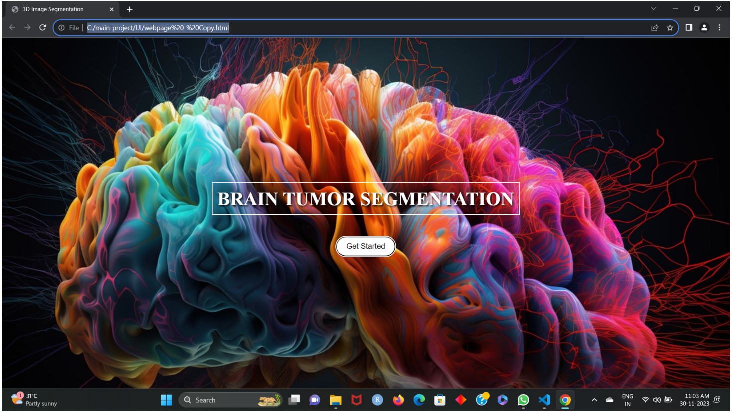


Figure 3: Opening page

UI Design

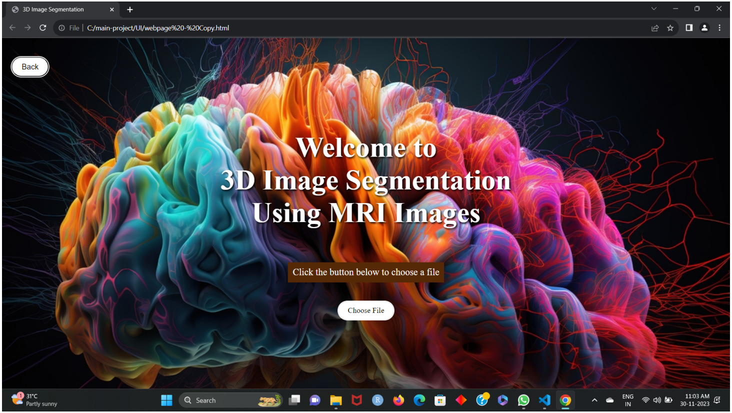


Figure 4: Choosing File

UI Design

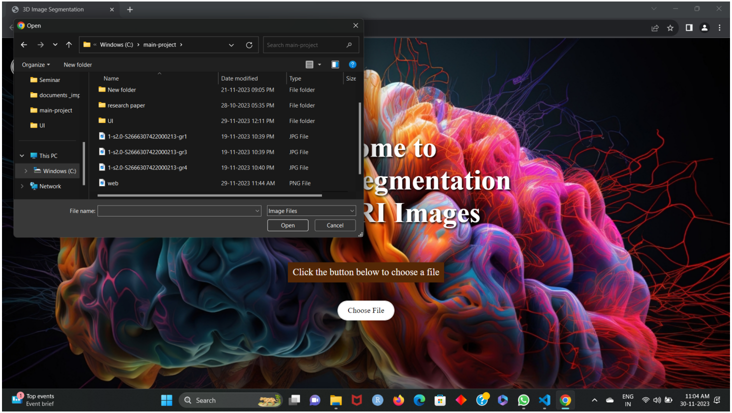


Figure 5: Opening file

Implementation Details

Data Collection:

- Collecting Brain Tumor Segmentation(BraTS2020) dataset.

Data Preparation:

- Preprocessing such as image resizing, normalization and data augmentation.
- Conduct stratified K-fold cross-validation for train-validation split, and segregate test data.

3D Unet model:

- Utilizes a 3D variant of the popular UNet architecture.

Implementation Details

Model Evaluation and Metrics:

- Employs various evaluation metrics to comprehensively assess model performance.
- Utilizes confusion matrices for detailed analysis of the model's predictions.

Visualization:

- 3D scatter plots for visualizing MRI scans and tumor segmentations.
- Visualizes metrics using bar plots.

Time Measurement:

- Efficiency Analysis aiding in profiling and optimization for better performance.

Implementation Details

Adding Additional Features:

- Tumor size estimation and Survival prediction,Tumor type classification

Code Optimization:

- Continual improvement in code efficiency and performance to ensure streamlined and optimized model execution.

Documentation:

- For enhanced code readability, maintainability, and comprehension, facilitating future modifications and extensions.

Result

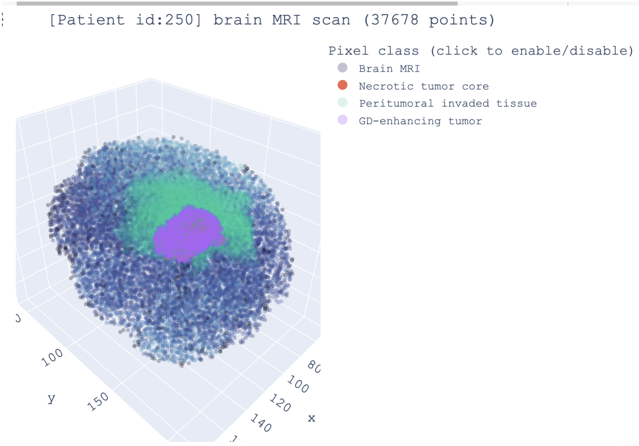


Figure 6: Segmented output

Result

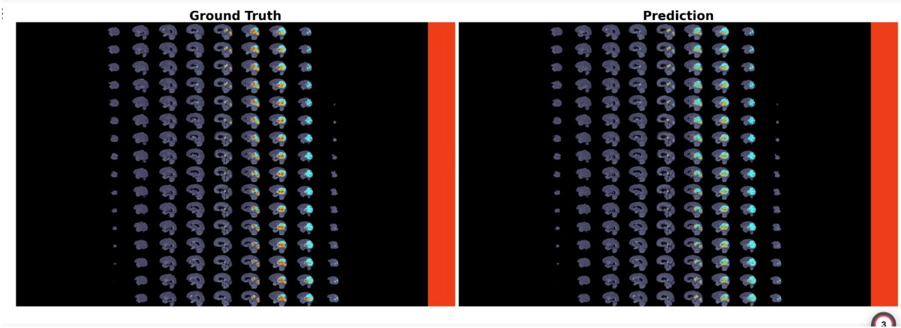
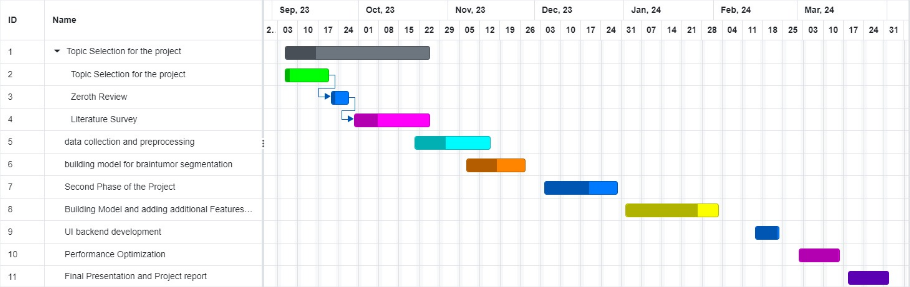


Figure 7: Visualizing the predicted segmented masks

Work to be done

- Adding additional features other than segmentation.
  - Tumor Type Classification
  - Tumor Size Estimation and Survival Prediction
- Evaluation of the added feature predictions.
- Work on improving the efficiency of the new model with different combination of loss-function and optimizers to get good results.

Gantt Chat



ID
Name
Sep, 23
Oct, 23
Nov, 23
Dec, 23
Jan, 24
Feb, 24
Mar, 24
2.. 03 10 17 24 01 08 15 22 29 05 12 19 26 03 10 17 24 31 07 14 21 28 04 11 18 25 03 10 17 24 31
1 Topic Selection for the project
2 Topic Selection for the project
3 Zeroth Review
4 Literature Survey
5 data collection and preprocessing
6 building model for braintumor segmentation
7 Second Phase of the Project
8 Building Model and adding additional Features...
9 UI backend development
10 Performance Optimization
11 Final Presentation and Project report

Timeline

- **October 2023**: Define project scope,objectives,and requirements,Complete Literature Review
- **November 2023**:Data preprocessing,Exploratory Data Analysis
- **December 2023**:Develop 3D Unet model for 3D brain tumor segmentation.Train the model with appropriate hyperparameter tuning.
- **January 2024**:Fine-tune the model for improved segmentation accuracy.Validate the model.
- **February 2024**:Document the entire project, including the model architecture.
- **March 2024**:Conduct final evaluations and testing.

Conclusion

- The brain tumor segmentation project represents a pivotal advancement in healthcare with its ability to achieve high accuracy, early detection, and improved accessibility.
- This project holds the potential to significantly enhance patient care, increase the likelihood of early interventions, and contribute to better treatment outcomes for individuals affected by brain tumors.

References I

[1] J. Chang, X. Zhang, M. Ye, D. Huang, P. Wang, and C. Yao, "Brain tumor segmentation based on 3d unet with multi-class focal loss," in *2018 11th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI)*, pp. 1–5, IEEE, 2018.

[2] J. Nodirov, A. B. Abdusalomov, and T. K. Whangbo, "Attention 3d u-net with multiple skip connections for segmentation of brain tumor images," *Sensors*, vol. 22, no. 17, p. 6501, 2022.

[3] P. Ahmad, S. Qamar, L. Shen, and A. Saeed, "Context aware 3d unet for brain tumor segmentation. arxiv 2020," *arXiv preprint arXiv:2010.13082*.

[4] W.-W. Lin, C. Juang, M.-H. Yueh, T.-M. Huang, T. Li, S. Wang, and S.-T. Yau, "3d brain tumor segmentation using a two-stage optimal mass transport algorithm," *Scientific reports*, vol. 11, no. 1, p. 14686, 2021.

References II

[5] Y. Ding, F. Chen, Y. Zhao, Z. Wu, C. Zhang, and D. Wu, "A stacked multi-connection simple reducing net for brain tumor segmentation," *IEEE Access*, vol. 7, pp. 104011–104024, 2019.

[6] T. Henry, A. Carre, M. Lerousseau, T. Estienne, C. Robert, N. Paragios, and E. Deutsch, "Brain tumor segmentation with self-ensembled, deeply-supervised 3d u-net neural networks: A brats2020 challenge solution. arxiv 2020," *arXiv preprint arXiv:2011.01045*.

[7] B. Erden, N. Gamboa, and S. Wood, "3d convolutional neural network for brain tumor segmentation," *Computer Science, Stanford University, USA, Technical report*, 2017.

[8] Z. Qian, L. Xie, and Y. Xu, "3d automatic segmentation of brain tumor based on deep neural network and multimodal mri images," *Emergency Medicine International*, vol. 2022, 2022.

[9] A. Chattopadhyay and M. Maitra, "Mri-based brain tumour image detection using cnn based deep learning method," *Neuroscience informatics*, vol. 2, no. 4, p. 100060, 2022.

[10] Z. Zhou, Z. He, and Y. Jia, "Afpnet: A 3d fully convolutional neural network with atrous-convolution feature pyramid for brain tumor segmentation via mri images," *Neurocomputing*, vol. 402, pp. 235–244, 2020.

[11] J. L. Rondo and E. M. Asto, "Brain tumor volumetric segmentation in multimodal mri using 3d convolutional neural networks," in *2021 IEEE XXVIII International Conference on Electronics, Electrical Engineering and Computing (INTERCON)*, pp. 1–4, IEEE, 2021.

[12] M. Sharif, U. Tanvir, E. Munir, M. Khan, and M. Yasmin, "Brain tumor segmentation and classification by improved binomial thresholding and multi-features selection. j ambient intell humaniz comput," *doi.org/10.1007/s1265*, pp. 2–018, 2018.

References IV

[13] S.-L. Jui, S. Zhang, W. Xiong, F. Yu, M. Fu, D. Wang, A. E. Hassanien, and K. Xiao, "Brain mri tumor segmentation with 3d intracranial structure deformation features," *IEEE intelligent systems*, vol. 31, no. 2, pp. 66–76, 2015.

[14] K. Vaishnavee and K. Amshakala, "An automated mri brain image segmentation and tumor detection using som-clustering and proximal support vector machine classifier," in *2015 IEEE international conference on engineering and technology (ICETECH)*, pp. 1–6, IEEE, 2015.

[15] H. Khotanlou, O. Colliot, J. Atif, and I. Bloch, "3d brain tumor segmentation in mri using fuzzy classification, symmetry analysis and spatially constrained deformable models," *Fuzzy sets and systems*, vol. 160, no. 10, pp. 1457–1473, 2009.

[16] D. Cobzas, N. Birkbeck, M. Schmidt, M. Jagersand, and A. Murtha, "3d variational brain tumor segmentation using a high dimensional feature set," in *2007 IEEE 11th international conference on computer vision*, pp. 1–8, IEEE, 2007.

THANK YOU