Brain Tumor Segmentation

Team Number - 12

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Problem Statement

- MRI scans face challenges in accurately segmenting brain tumors due to limitations in existing methods.
- .Brain tumor segmentation is crucial for medical image analysis, especially in distinguishing between high-grade gliomas (HGG) and low-grade gliomas (LGG).
- Existing segmentation models often experience redundant computation due to skip connections in the U-Net architecture.
- This redundancy slows down segmentation and can lead to inaccuracies in classification.

Objective/Motivation

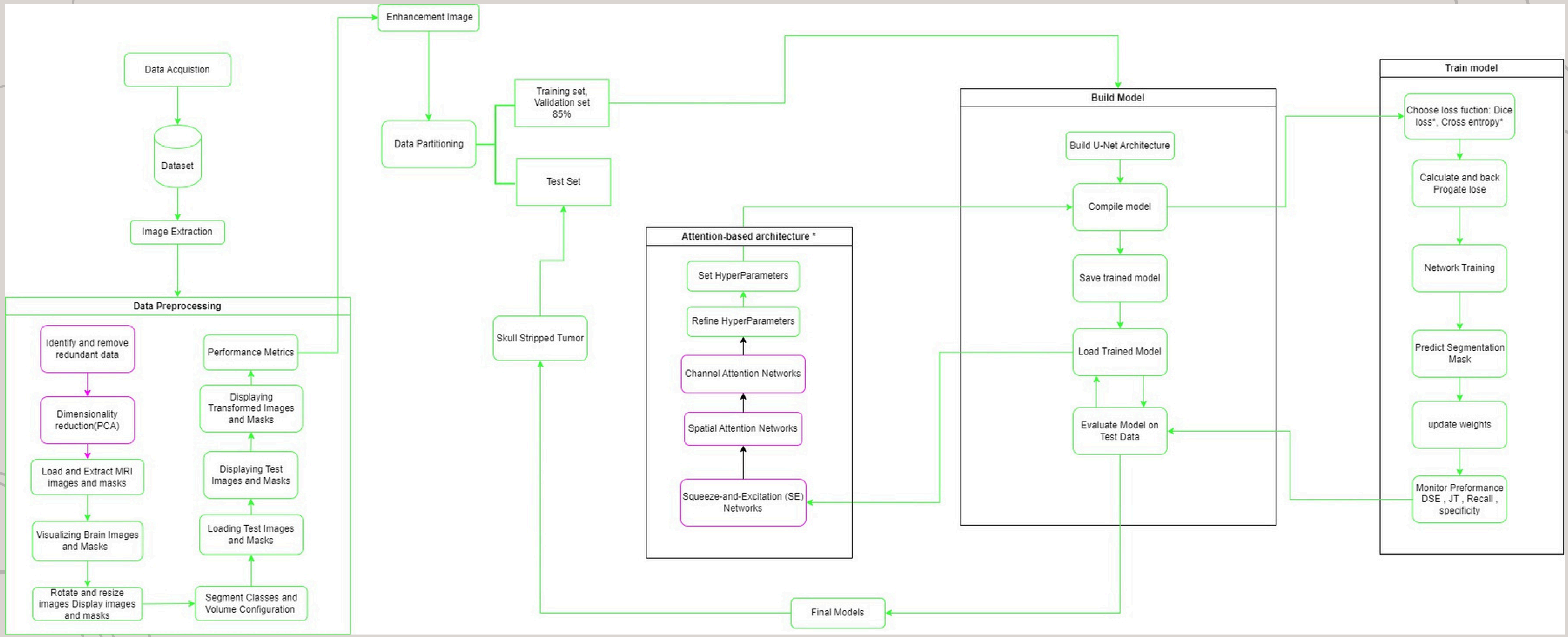
- Improve the accuracy and efficiency of brain tumor segmentation, specifically for distinguishing between high-grade gliomas (HGG) and low-grade gliomas (LGG).
- Address the issue of redundant computation in existing models, which can lead to slower processing times and potential inaccuracies in classification.
- Enhance treatment planning and monitoring of disease progression in neuroimaging through more accurate segmentation of brain tumors.
- Streamline the medical imaging workflow by developing a model that can effectively classify HGG and LGG while minimizing redundant computation.
- Ultimately, improve patient outcomes through more accurate and efficient medical image analysis techniques.

Gap Analysis

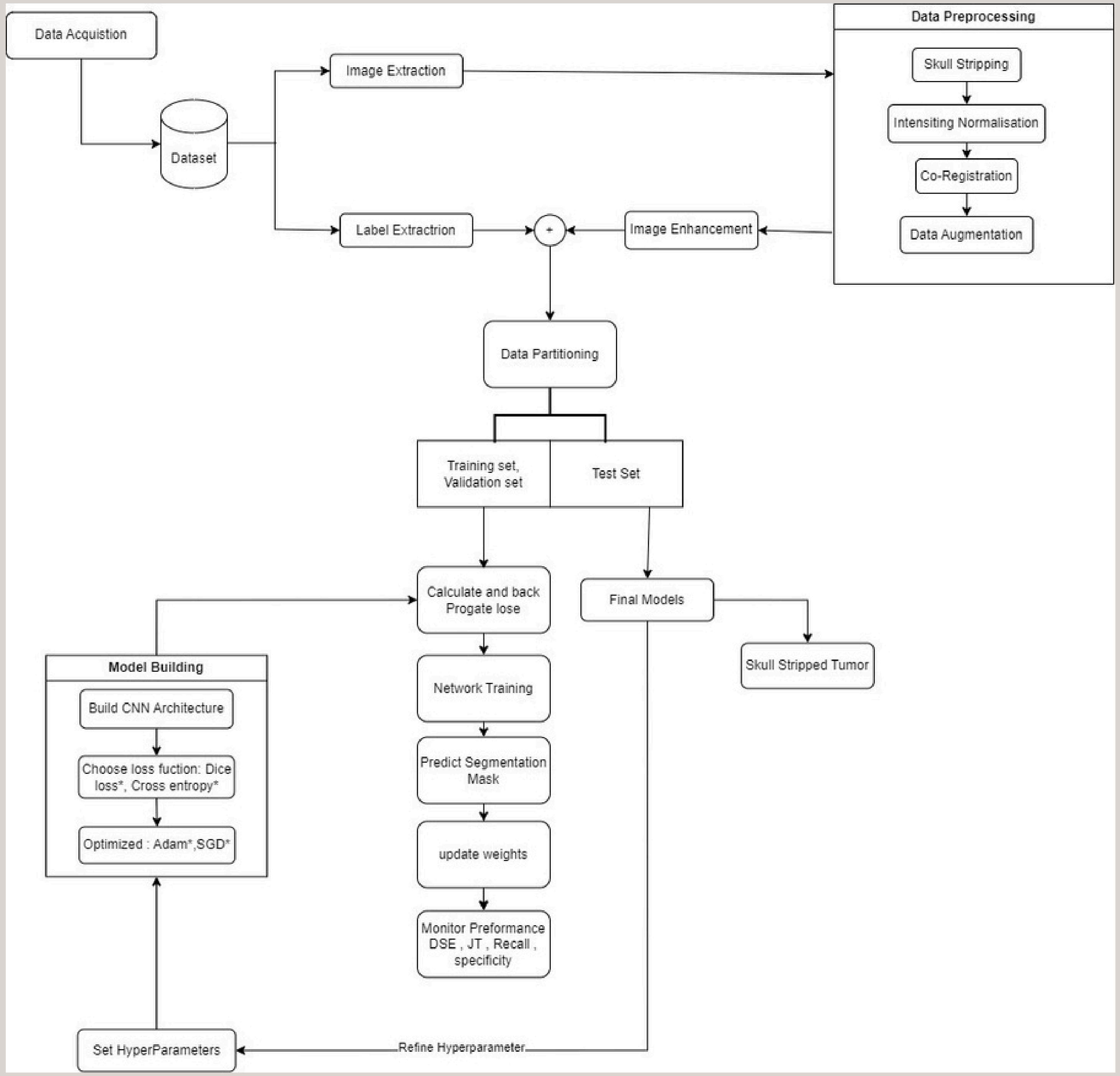
- **Handling of tumor heterogeneity** - Tumors can exhibit diverse characteristics within a single lesion such as variations in shape, texture and intensity. the current segmentation methods may not adequately capture heterogeneity, leading to inaccuracies in delineating tumor boundaries.
- **Difficult in segmentation** - The variations in signal intensity between tumor and healthy tissue can be subtle, especially on T1-weighted images. This can make it challenging to accurately segment the tumor boundary, leading to either underestimation (missing parts of the tumor) or overestimation (including healthy tissue).
- **Accurate identification of tumor margin** - Precise definitions of tumor margins is crucial for treatment planning and monitoring. However, existing algorithms may fail to accurately differentiate tumor tissue and surrounding healthy brain structure.

- **Redundancy in Skip Connections:** Adding an attention mechanism to U-Net models for brain tumor segmentation reduces redundant computation, improving efficiency and accuracy.
- **Data Visualization Challenge of a 3D Dataset:** Performing a 3D Exploratory Data Analysis (EDA) for brain tumor segmentation was essential due to the dataset's 3D nature, which made visualization challenging. This analysis provided deeper insights into the dataset's characteristics, aiding in understanding patterns and features critical for segmentation.

Block Diagram
U-net:-



V-net


Data Acquistion
Dataset
Image Extraction
Label Extractrion
+
Image Enhancement
Data Preprocessing
Skull Stripping
Intensiting Normalisation
Co-Registration
Data Augmentation
Data Partitioning
Training set, Validation set
Test Set
Calculate and back Progate lose
Final Models
Skull Stripped Tumor
Model Building
Build CNN Architecture
Choose loss fuction: Dice loss*, Cross entropy*
Optimized : Adam*,SGD*
Network Training
Predict Segmentation Mask
update weights
Monitor Preformance DSE , JT , Recall , specificity
Set HyperParameters
Refine Hyperparameter

Detailed Design

1. Segment Classes and Volume Configuration:
   - Segment classes - Define the classes for tumor segmentation, where each class represents a specific region of interest in the brain.
   - Volume configuration - Specify the number of slices per volume and the range of slices to use, considering the skip of the initial and final slices to avoid irrelevant information.
2. Data import and extraction
3. Loading images and segmentation masks
4. Preprocessing images
5. Visualizing brain images and their corresponding masks
6. Performance metrics: Compute metrics such as accuracy, mean IoU (Intersection over Union), and Dice coefficient to quantitatively assess the model's performance in segmenting brain tumors.

7. U-net Architecture with Attention Mechanism:

- Contracting Path: Two 3x3 convolutional layers with ReLU activation and same padding, followed by max pooling. This is repeated with increasing filters (32, 64, 128, 256, 512). Dropout is applied after the last convolutional layer.
- Expanding Path: Up-sampling followed by a 2x2 convolutional layer with ReLU activation and same padding. The up-sampled feature map is concatenated with the corresponding feature map from the contracting path. Two 3x3 convolutional layers with ReLU activation and same padding are applied. This is repeated with decreasing filters (256, 128, 64, 32).
- Attention Mechanism: Before concatenation in the expanding path, an attention mechanism is applied to the feature maps from the contracting path. The attention mechanism ensures that only relevant features are passed on to the expanding path, reducing redundancy and improving segmentation accuracy.
- Final Convolution: A 1x1 convolutional layer with SoftMax activation produces the final segmentation map.

8. Splitting Test and Train Data: Data is split into training, validation, and test sets using a predefined split ratio.

- Test set - 15%
- Training and Validation set - 85%

9. Training the model with callbacks: The model is trained using the fit method with callbacks for model checkpointing, early stopping, and CSV logging.

10. Loading the trained model: The trained model can be loaded from the saved weights file.

11. Evaluating the performance on the test set: For evaluating the model's performance on the test set, the Adam optimizer is employed along with several performance metrics. These metrics encompass accuracy, mean Intersection over Union (IoU), dice coefficient, precision, sensitivity, specificity, and specific dice coefficients for distinct classes. The model's performance on the test set will be assessed using these metrics.

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Performance Metrics

- **Loss:** A measure of how well a model performs on a specific data point. Lower loss indicates better performance during training. In your case, the loss function is dice coefficient loss, which is commonly used in medical image segmentation tasks.
- **Accuracy:** Represents the proportion of correct predictions made by the model. A higher accuracy indicates the model is making fewer mistakes.

  Accuracy = (TP + TN) / (Total Pixels)
- **Mean IoU (Intersection over Union):** This metric calculates the average overlap between the predicted segmentation and the ground truth (actual segmentation). It ranges from 0 (no overlap) to 1 (perfect overlap).

  IoU = TP / (TP + FP + FN)
- **Dice Coefficient:** Another metric to assess segmentation quality. It considers both the overlap and the area covered by the prediction and the ground truth. A dice coefficient of 1 indicates perfect overlap, and 0 means no overlap.

  Dice Coefficient (DSC) = 2 * (TP / (TP + FP + FN))
- **Precision:** Out of all the positive predictions made by the model, how many were actually correct (true positives)? A high precision indicates the model is rarely making false positive errors.

  Precision = TP / (TP + FP)

- **Sensitivity (Recall):** Out of all the actual positive cases (present in the ground truth), how many did the model correctly identify (true positives)? A high sensitivity indicates the model is not missing many positive cases (false negatives).

  Sensitivity = TP / (TP + FN)

- **Specificity:** How good is the model at identifying true negatives? Specificity measures the proportion of negative cases the model correctly classified (correctly identified as negative). A high specificity means the model is not incorrectly classifying negative cases as positive.

  Specificity = TN / (TN + FP)

- **Dice Coefficient (Necrotic/Edema/Enhancing):** These are individual dice coefficient scores for different tissue types the model is segmenting. They provide a more detailed breakdown of the model's performance on each specific class.

30% Project Review Performance Metrics

U-net

Performance Metrics	Training	Validation	Test
Loss	0.0216	0.0187	0.0166
Accuracy	0.9933	0.9939	0.9947
Mean IoU	0.8261	0.8167	0.809
Dice Coefficient	0.6176	0.6622	0.6525
Precision	0.9938	0.9942	0.9949
Sensitivity	0.9918	0.9926	0.9933
Specificity	0.9979	0.998	0.9983
Dice Coefficient (Necrotic)	0.5884	0.6277	0.6647
Dice Coefficient (Edema)	0.7057	0.7518	0.759
Dice Coefficient (Enhancing)	0.7186	0.7847	0.7758

V-net

Performance Metrics	Training	Validation
Loss	0.0453	0.1664
Accuracy	0.9869	0.9848
Mean IoU	0.4556	0.4352
Dice Coefficient	0.4738	0.2992
Precision	0.9899	0.986
Sensitivity	0.9827	0.9842
Specificity	0.9972	0.9954
Dice Coefficient (Necrotic)	0.1797	0.032
Dice Coefficient (Edema)	0.4106	0.1007
Dice Coefficient (Enhancing)	0.3096	0.0698

90% Project Review Performance Metrics

Attention U-Net for HGG

Metric	Training	Validation	Testing
Loss	0.0728	0.0738	0.0767
Accuracy	0.9842	0.9831	0.9811
Mean IoU	0.7031	0.7648	0.6328
Dice Coefficient	0.2637	0.2635	0.2657
Precision	0.9841	0.983	0.981
Sensitivity	0.9841	0.9831	0.981
Specificity	0.9947	0.9944	0.9937
Dice Coeff (Necrotic)	0.0297	0.021	0.0288
Dice Coeff (Edema)	0.0957	0.0889	0.0939
Dice Coeff (Enhancing)	0.0425	0.0351	0.0446

Attention U-Net for LGG

Metric	Training	Validation	Testing
Loss	0.0843	0.0743	0.0767
Accuracy	0.9804	0.9834	0.9823
Mean IoU	0.4847	0.4202	0.3911
Dice Coefficient	0.2659	0.2677	0.2641
Precision	0.9803	0.9832	0.9822
Sensitivity	0.9803	0.9832	0.9822
Specificity	0.9934	0.9944	0.9941
Dice Coeff (Necrotic)	0.0854	0.1055	0.0663
Dice Coeff (Edema)	0.0955	0.1184	0.1003
Dice Coeff (Enhancing)	0.0085	0.0101	0.009

Sample Test Cases

Dataset Partitioning:

- Segmented the dataset into distinct subsets: training, validation, and test sets.
- Ensured that the model's performance was evaluated on unseen data, specifically the test set.

Image Modality Usage:

- Employed a variety of MRI image modalities, including T1, FLAIR, T2, and T1CE.
- Utilized these modalities to provide comprehensive input for the model.

Accuracy Achievement:

- Achieved a high level of accuracy in generating image masks for each modality.
- Ensured that the model accurately segmented the various tumor regions in the MRI images.

Dice Coefficient Calculation:

- Calculated the Dice coefficient for the necrotic, edema, and enhancing tumor regions.
- Used the Dice coefficient as a measure of the model's segmentation performance, ensuring accurate delineation of tumor subregions.

Model Comparisons:

- Compared the performance of the U-Net model with other state-of-the-art segmentation models to validate its effectiveness for brain tumor segmentation.

Testing on Small Dataset Size:

- Conducted model testing on a limited dataset of 3GB to assess performance, accuracy, and efficiency.
- Evaluated resource utilization and generalization capabilities of the model with insights for scalability to larger datasets.

Comparing U-Net and Attention U-Net for Accuracy Improvement:

- Ran tests to measure the accuracy change when transitioning from a U-Net to an Attention U-Net.
- Focused on reducing redundant low-level feature extraction to improve segmentation accuracy.
- Results provide insights into the effectiveness of attention mechanisms in enhancing segmentation performance.

30% Project Completion

- **U-Net Accuracy:** The U-Net achieved a test accuracy of approximately 99.47% on the BraTS 2021 dataset.
- **Dataset:** BraTS 2021 is a standard benchmark dataset for brain tumor segmentation tasks. It includes multi-modal MRI scans with segmentations for whole tumor, tumor core, and edema.
- **Comparison between U-Net and V-Net:** U-Nets are specifically designed for segmentation tasks, while CNNs are more general-purpose. Comparing the U-Net's performance (99.47% accuracy) with the V-Net's results (98.69) would determine which model is better suited for this task. By this we can say U-net performs relatively better and we will be working on this to ensure a good accuracy on smaller dataset

90% Implemented Features:-

- **Achieving High Accuracy with Limited Data:** Successfully attained high segmentation accuracy despite working with a small-sized dataset, demonstrating the effectiveness of the implemented methodologies.
- **Utilizing U-Net Architecture:** Leveraged the U-Net architecture, a proven framework for medical image segmentation tasks, to achieve the main segmentation objective.
- **Integration of Advanced Deep Learning Algorithms:** Incorporated cutting-edge deep learning algorithms, such as attention mechanisms and distance-wise mechanisms, to further enhance segmentation accuracy and refine the results.
- **Addressing Glioma Classification:** Implemented strategies to accurately classify gliomas into low grade and high grade, showcasing a comprehensive approach to brain tumor segmentation.
- **Streamlit App Development:** Created a user-friendly Streamlit application for easy interaction and visualization of brain tumor segmentation.
- **3D Exploratory Data Analysis (EDA):** Conducted a comprehensive 3D EDA to better understand and utilize the dataset for segmentation.

Thank You