# Brain Tumor Segmentation & Explainability Project Report

## 1. Introduction

Brain tumor segmentation in MRI scans is a vital step in diagnosis and treatment planning. This study implements and compares three architectures—Standard U-Net, Attention U-Net, and a Patch-based MLP—on the BraTS18 dataset. To understand why each model makes its decisions, we apply three XAI methods: Grad-CAM, Saliency Maps, and Permutation Importance.

## 2. Dataset

- Source: MICCAI BraTS18 challenge  
- Modalities: T1, T1-Gd (contrast-enhanced), T2, FLAIR  
- Labels:  
 • Whole Tumor (WT)  
 • Tumor Core (TC)  
 • Enhancing Tumor (ET)  
- Volume Count: 285 patient studies  
- Split: 80% training, 20% validation

## 3. Preprocessing & Exploratory Data Analysis

1. Intensity Normalization: Each modality scaled to [0,1] using min–max per volume.  
2. Resizing & Slicing: Volumes resampled to 112×112×N, then extracted as 2D slices.  
3. Class Imbalance: Tumor pixels ≈ 5% of all voxels. Mitigated via on-the-fly data augmentation (flips, rotations, intensity jitter).  
4. EDA Findings:  
 - Tumor intensities overlap with non-tumor; normalization critical.  
 - Distribution of slice counts per patient varies; pad/truncate to fixed number of slices.

## 4. Model Architectures

4.1 Standard U-Net  
- Encoder: Four downsampling blocks of (Conv → ReLU → Conv → ReLU → MaxPool)  
- Bottleneck: Two convolutional layers  
- Decoder: Four upsampling blocks with concatenated skip-connections  
- Output: 1×1 convolution + softmax over four classes  
  
4.2 Attention U-Net  
- Same backbone as U-Net, with attention gates on skip-connections to focus on tumor regions.  
  
4.3 Patch-based MLP  
- Patch Extraction: Non-overlapping 7×7 patches.  
- Embedding: Flattened patches through Dense layers.  
- Reconstruction: Reassemble patches and upsample back to 112×112.

## 5. Training Configuration

- Optimizer: Adam (learning rate 1e-4)  
- Loss: Combined Categorical Cross-Entropy + Dice Loss  
- Batch Size: 16  
- Epochs: Up to 50, with EarlyStopping on validation Dice (patience=8)  
- Callbacks: ModelCheckpoint, ReduceLROnPlateau

## 6. Evaluation Metrics

- Dice Coefficient: Overlap between prediction and ground truth.  
- Intersection over Union (IoU).  
- Pixel Accuracy: Overall correct pixels.  
- Inference Time: ms per slice.

## 7. Results

| Model | Dice (val) | IoU (val) | Pixel Acc. | Inference Time |  
|---------------------|------------|-----------|------------|----------------|  
| Standard U-Net | 0.82 | 0.75 | 0.93 | 25 ms/slice |  
| Attention U-Net | 0.85 | 0.78 | 0.95 | 30 ms/slice |  
| Patch-based MLP | 0.77 | 0.70 | 0.91 | 15 ms/slice |

## 8. Explainability Analyses

- Grad-CAM: Attention U-Net shows tight heatmaps around tumor boundaries; Patch-MLP activations are more diffuse.  
- Saliency Maps (Attention U-Net): Highlight high-contrast edges critical for prediction.  
- Permutation Importance (Patch-MLP): Reveals most influential spatial regions by shuffling patches.

## 9. Conclusions

- Attention U-Net achieves best segmentation performance.  
- Patch-based MLP offers faster inference at slight accuracy cost.  
- Standard U-Net remains a strong baseline.

## 10. Future Work

- Implement 3D U-Net to leverage volumetric context.  
- Explore transformer-based segmentation (e.g., UNETR).  
- Add more XAI techniques (Integrated Gradients, SHAP).

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