Brain Tumors Classification & Segmentation

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Introduction

Neural networks, integrated into this project using standard deep learning frameworks, provide a foundational component for medical image analysis. Two key tasks in this domain are **segmentation** and **classification**, both essential for accurate diagnosis and treatment planning. **Segmentation** involves delineating specific structures within an image—such as tumors in brain MRI scans—by assigning a label to each pixel, thereby enabling precise localization and volume estimation of pathological regions. **Classification**, on the other hand, focuses on assigning a diagnostic category to an image or region, such as distinguishing between different types of brain tumors (e.g., glioma, meningioma, pituitary tumor) or identifying whether a scan indicates a healthy or abnormal condition. These tasks are challenging due to the high variability in tumor shape, size, and location, as well as differences in image quality across patients and scanners.

The inclusion of neural networks in this project serves three primary purposes: (1) to facilitate automated and accurate analysis of MRI brain scans, (2) to ensure consistency and efficiency in detecting and segmenting tumors, and (3) to support the development of scalable diagnostic tools suitable for integration into healthcare systems. The application of neural networks in this context demonstrates their ability to process complex imaging data, identify tumor characteristics, and provide detailed outputs that support clinical decision-making. These models, trained on labeled MRI datasets, enhance diagnostic precision by reducing the likelihood of human error and accelerating the analysis process. Their implementation follows widely accepted standards for neural network design in medical imaging, contributing to the advancement of AI-driven diagnostic systems in neuro-oncology.

Methods

1) **Data Collection & Preprocessing**
- Used publicly available datasets (BraTS) containing annotated MRI scans of the brain.
- Preprocessing steps included:
  - Resizing and normalizing MRI images.
  - Skull stripping and noise reduction.
  - Data augmentation techniques (e.g., rotation, flipping) to improve model generalization.

1) **Tumor Segmentation**
- The Attention U-Net model from MONAI is used, incorporating attention mechanisms and skip connections.
- Output: Binary segmentation masks highlighting tumor regions.
- Metrics : Dice Score or IOU.

3) **Tumor Classification**
- Developed a CNN-based classifier to predict tumor type:
  - **Glioma Tumor**
  - **Pituitary Tumor**
  - **Meningioma**
  - **No Tumor**
- Achieved classification through transfer learning or training from scratch.
- Metrics : Accuracy and F1-Score

4) **Tumor Proportion Estimation**

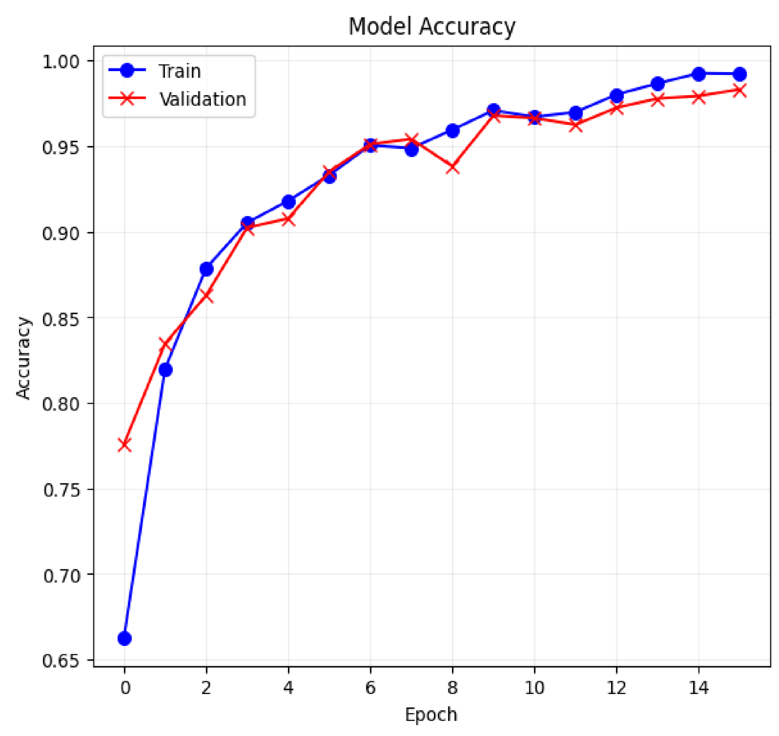
Calculated by dividing the number of white pixels in the binary mask over the whole mask size (height * width) to compute the tumor proportion in this 2D MRI scan

5) **Brain 3D Reconstruction**
- Use our segmentation model to segment MRI scans, then compute the overlapping volume of the MRI slices and tumor masks by stacking them along the z-axis.
- Provide the tumor volume in cm3

Results

Table I: Results of Classification model

Model	Training accuracy	Validation accuracy	Testing accuracy	Testing F1-score
CNN	99.23	98.32	98.32	98.32



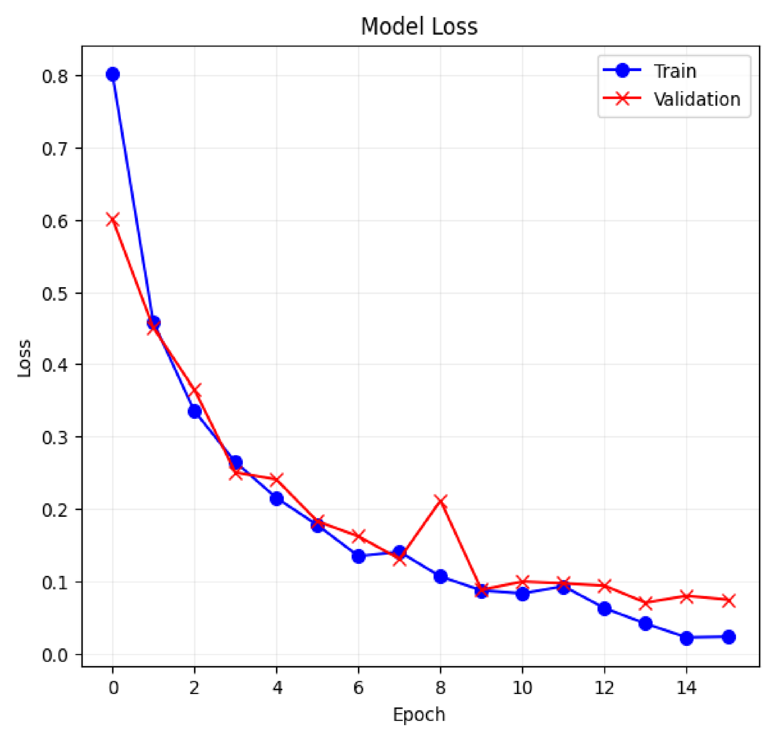


Table 2: Results of Segmentation Model:

Model	Val dice	Val IOU	Test dice	Test IOU	Augmentation
Attention U-Net (1M Parameter)	86.47	76.34	86.95	79.47	1. Rotate and Resize 2. Vertical flipping 3. Normalization 4. Bright contrast 5. Gaussian noise

Brain 3D Reconstruction Results:

This is a rule-based 3D brain reconstruction process that does not involve any AI models. It is performed by stacking the MRI scans along with their corresponding masks along the z-axis to compute the 3D object. The only evaluation metric used is the **Contrast-to-Noise Ratio (CNR)**, which measures how clearly the brain volume can be distinguished from the tumor volume. A **CNR** value of 2 or higher is considered acceptable. In our case, the mean **CNR** across **55** samples was **2.75**.

Conclusions

This project presents an automated system for brain tumor classification, segmentation, and 3D reconstruction from MRI scans to support clinical diagnosis. A custom CNN accurately classifies tumor types (Glioma, Meningioma, Pituitary, or No Tumor) with 98.32% test accuracy and F1-score. For segmentation, an Attention U-Net detects tumor regions and estimates their proportion within each slice, achieving a Dice score of 86.95% and IoU of 79.47%. Additionally, the system reconstructs a 3D brain model from MRI slices, enabling better visualization of tumor size and spatial location.

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