NeuroAssist:Multi-Class Brain Tumor Detection Using Lightweight Models

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GitHub link: http://github.com/21Afnan/TumorSense-AI

Video link: https://drive.google.com/drive/folders/1aMQkKk6S9vjQyigBk3R-nVf0CUjUyb6r?usp=sharing

1. Introduction

Brain tumors are serious neurological disorders that can impact brain function and patient survival. Early and accurate detection is essential for effective treatment, such as surgery or radiotherapy.

Magnetic Resonance Imaging (MRI) is the preferred method for diagnosis due to its high-quality soft-tissue images and non-invasive nature. However, manual analysis by radiologists is time-consuming and can vary based on experience.

Deep learning, especially Convolutional Neural Networks (CNNs), helps automate this process by detecting patterns in MRI scans quickly and consistently.

This project uses lightweight deep learning models to classify brain MRI images into four classes:

- Glioma
- Meningioma
- Pituitary Tumor
- No Tumor

This project presents a lightweight multi-class brain tumor detection system using MRI images. A basic CNN is employed as a baseline model, while ResNet-18 with transfer learning serves as the main classifier to balance accuracy and computational efficiency. The system classifies images, aiming for high accuracy with low computational cost, making it suitable for resource-constrained clinical settings

.2. Literature Review

Deep learning has revolutionized brain tumor classification from MRI images. CNNs excel at automatically extracting features like edges, textures, and tumor shapes without manual input.

Many studies use complex, deep models for high accuracy, but these require powerful hardware and long training times, limiting real-world use.

Lightweight models with transfer learning offer a better balance. Pretrained networks adapt general features from large datasets (like ImageNet) to medical images efficiently.

ResNet-18 stands out as a lightweight yet powerful option for multi-class brain tumor tasks, achieving strong results with lower resources. This supports our choice of models.

3. Solution Approach

We used two lightweight deep learning models for comparison and classification:

Model	Type	Why Used?	Key Features	When/How Applied	Example Benefit
Custom CNN	Baseline (from scratch)	To establish basic performance of a simple CNN on MRI data	Convolutional layers for feature extraction Pooling for downsampling Fully connected layers for classification	Trained from scratch on the dataset Used as benchmark to compare with advanced models	Simple and fast to train Shows fundamental deep learning capability (e.g., achieves ~90-95% accuracy in similar tasks)
ResNet-18	Primary (Transfer Learning)	Best balance of accuracy and efficiency Lightweight for clinical deployment	18 layers with residual connections (prevents vanishing gradients) Pretrained on ImageNet	Fine-tuned: Replaced final layer with 4-class output Frozen early layers, trained later ones	Higher accuracy (typically 95-99% in literature) Faster convergence Low computational cost

These models classify images into: Glioma, Meningioma, Pituitary Tumor, or No Tumor.

The system automatically classifies brain MRI images using the above models.

- **Data Preprocessing**: Images resized to uniform size (e.g., 224x224), normalized, and augmented (rotations, flips, zooms) to improve generalization and reduce overfitting.
- **Baseline Model (Custom CNN)**: Learns features directly from MRI data.
- **Primary Model (ResNet-18)**: Uses transfer learning for better feature adaptation to medical images.

Focus: High accuracy with lightweight design for easy deployment.

4. Implementation

Built using Python and PyTorch.

- **Dataset**: Public brain tumor MRI dataset (e.g., from Kaggle/Figshare) with ~7,000-12,000 images across 4 classes. Split into training, validation, and testing.
- **Preprocessing & Augmentation**: Resizing, normalization, random transformations.
- **Training**:
  - Optimizer: AdamW (with weight decay for regularization)
  - Loss: Cross-Entropy (suitable for multi-class)
  - Monitored validation accuracy and confusion matrix.
- **Evaluation**: Accuracy, confusion matrix to identify class-specific performance.

5. Results and Discussion

- Custom CNN (baseline): Achieved good accuracy, but lower than transfer learning model.
- ResNet-18: Superior performance due to pretrained features and residual blocks. Typically reaches 95-99% accuracy on similar datasets (based on literature).
- Strengths: ResNet-18 handles subtle tumor differences better.
- Challenges: Some classes (e.g., similar-looking tumors) may confuse the model, shown in confusion matrix.
- Overall: Lightweight models prove effective for reliable clinical assistance.

6. Conclusion

This project demonstrates that lightweight models like ResNet-18 with transfer learning can accurately classify multi-class brain tumors from MRI images. They offer high performance with low resources, making them practical for real-world diagnosis. Future work can include more datasets or model optimizations.