Brain Tumors Classification and Segmentation

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Abstract—Brain tumors are among the most challenging medical conditions to diagnose and treat, often requiring accurate classification and precise identification of the tumor's size and location. This project addresses these challenges by leveraging deep learning techniques to classify brain Magnetic Resonance Imaging images into four categories: glioma, meningioma, pituitary tumor, and no tumor. In addition, it involves tumor segmentation to estimate the tumor's size and 3D reconstruction of brain images to support further analysis. The proposed solution employs convolutional neural networks for classification and a U-Net architecture for segmentation of tumor regions, using corresponding mask images alongside MRI scans. Post-processing techniques are used to calculate tumor volume from the segmented regions. Furthermore, 3D reconstruction methods are applied to generate a comprehensive view of the tumor in a three-dimensional context, aiding in surgical planning and treatment evaluation . The results demonstrate high accuracy in both classification and segmentation tasks, providing a reliable method for tumor detection and size estimation. The 3D reconstruction enhances diagnostic capabilities by offering detailed visualization of the tumor. This AI-driven approach contributes to early diagnosis and improved clinical decision-making . Ultimately, the model developed in this project advances the field of medical image analysis by offering an automated tool for brain tumor classification, segmentation, and 3D reconstruction. It is designed with potential deployment in mobile applications, aiming to make advanced tumor analysis more accessible to healthcare professionals.

Keywords—brain tumor classification, segmentation, 3D reconstruction, deep learning, Convolution Neural Network, U-Net, MRI.

I. INTRODUCTION

Neural networks, integrated into this project using standard deep learning frameworks, provide a foundational component for medical image analysis. Their inclusion 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 .

II. BACKGROUND

A. Deep Learning in Modern Applications

Deep learning has become a dominant approach in machine learning, surpassing traditional techniques like random forests and XGBoost. Its impact spans numerous industries, driving breakthroughs in speech recognition, image classification, and object detection. In medical domains, deep learning achieves cutting-edge results in critical tasks like brain tumor detection and segmentation. Key areas benefiting from these advances include:

- **Natural Language Processing (NLP)**: Powering applications from automated news generation and real estate transaction analysis to financial risk detection and psychiatric behavior understanding. Transformers and RNNs are fundamental to modern NLP systems like ChatGPT.
- **Computer Vision (CV)**: Revolutionizing image analysis through CNNs.
- **Other Domains**: Enhancing software development, facial expression recognition, and credit risk management.
  Despite rapid growth, security vulnerabilities like Backdoor/Trojan attacks require ongoing attention. This paper focuses on CNN architectures for brain tumor classification, evaluating pretrained models (MobileNetV2, EfficientNet-B0, ResNet-18, VGG16) and introducing MobileNet-BT—a customized variant with superior accuracy.

B. CNN:

CNNs form the backbone of modern computer vision systems. Their architecture comprises four key components:

1. *Convolutional Layers*: Apply learnable kernels to detect spatial patterns (edges, textures) through sliding window operations.
2. *Pooling Layers*: Reduce feature map dimensionality to preserve essential features while mitigating overfitting.
3. *Activation Functions*: Introduce non-linearity (e.g., ReLU) to enable complex pattern recognition and address vanishing gradients.
4. *Fully Connected Layers*: Generate final predictions by synthesizing extracted features.

CNNs excel in medical imaging applications, including:

- Image reconstruction and noise reduction
- Super-resolution reconstruction
- Early detection of abnormalities like nodules Their ability to learn hierarchical features makes them indispensable for tasks like brain tumor analysis in MRI scans.

C. Brain Tumor Types:

1. *Pituitary Tumors*
   These common benign growths originate in the pituitary gland. Though non-cancerous, they disrupt hormone regulation (prolactin, growth hormone, ACTH), causing systemic imbalances. The pituitary tumor MRI-based image can be found in Fig.1 below.
2. *Meningiomas*
   The most prevalent primary intracranial tumors. Often classified as benign, they nevertheless cause significant morbidity through neurological deficits, seizures, and reduced quality of life. The meningioma tumor MRI-based image can be found in Fig.1 below.
3. *Gliomas*
   The dominant malignant brain tumor type. Classified across four grades (I–IV), grade IV gliomas (glioblastomas) are highly aggressive and frequently recurring. The MRI-based image of the glioma tumor can be found in Fig.1 below

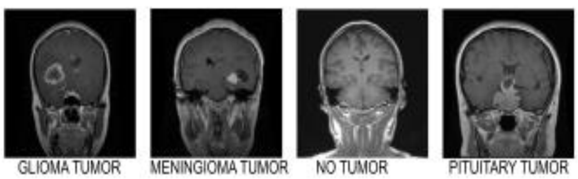


Fig. 1. Brain Tumor Types

III. RELATED WORK

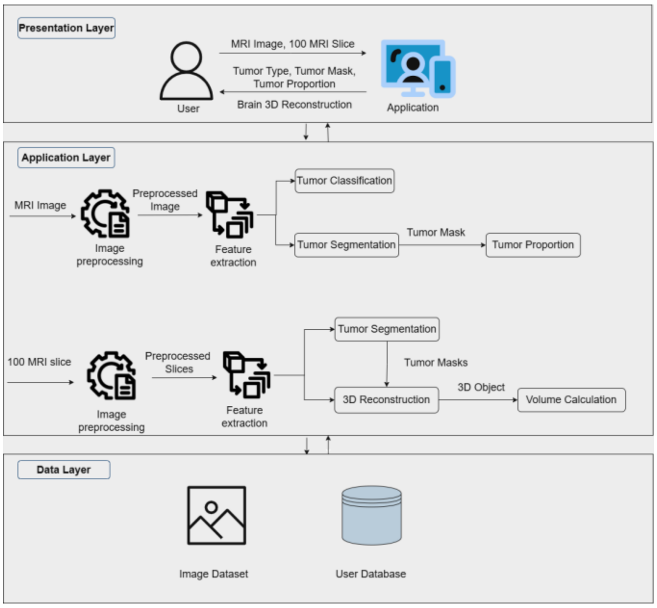
A. Classification

Title	*Model Name*	*Performance Measure*	*Accuracy(%)*
Deep Learning in Medical Image Classification from MRI-based Brain Tumor Images	MobileNet-BT	1. Accuracy 2. Precision 3. Recall 4. F1-Score 5. *Avg Loss*	1. *99.2* 2. 99.2 3. 99.2 4. 99.2 5. 0.0342
Classification of MRI Brain Tumor Images using Deep Learning Segment Anything Model and DCNN	*Coca*	1. Accuray 2. Precision 3. Recall 4. F1-Score	1. *97.6* 2. 99. 3. 97.2 4. 98.1
A Robust MRI-Based Brain tumor Classification via hybrid deep learning Technique	*Majority Voting Technique (GoogleNet, SqueezeNet, AlexNet, NasNet, ShufeNet)*	1. Accuracy 2. Precision 3. *F1-Score*	1. *99.3* 2. 99.9 3. 98.9

B. Segmentation:

Title	*Model Name*	*Performance Measure*	*Accuracy(%)*
Brain Tumor Segmentation from MRI Images using Deep Learning Techniques	Recurrent Residual U-Net	1. *Mean IOU* 2. Dice Score	1. 84.9 2. 86.6
Tumor Segmentation for Brain Tumor Using Combination of Deep Learning and Machine Learning Algorithms.	UnetVGG19	1. *Mean IOU* 2. Mean Dice	1. 79.3 2. 96.2
Medical Image Analysis for Tumor Segmentation Using U-Net Variants	Residual UNET	1. *Mean IOU* 2. Dice Score	1. 79 2. 86

IV. SYSTEM ARCHITECTURE



A. Data Layer

Responsible for data storage and retrieval.

1) *Image Dataset:*
   - Stores raw MRI images and preprocessed data.
   - May include labeled datasets for training ML models.

2) *User Database:*
   - Manages user profiles and authentication credentials.
   - Tracks user-specific data access permissions.

B. Application Layer Components

1) *Image Preprocessing*
   - *Applies standardization to both subsequent paths:*
     - *Noise reduction, intensity normalization*
   - ***Output**: Clean, standardized MRI image.*
2) *Tumor Segmentation Path*
   - ***Segmentation Model**:*
     - *Architecture: Attention unet.*
     - *Input: Preprocessed MRI image*
     - *Output: Binary tumor mask (pixel-wise tumor localization)*
3) *Tumor Classification Path*
   - ***Classification Model**:*
     - *Architecture: CNN.*
     - *Input: Same preprocessed MRI image (not the segmentation mask).*
     - *Output: Tumor type (e.g., "glioma", "meningioma, Pituitary")*
4) *3D Reconstruction*
   - ***Tumor Volume Calculation**:*
     - *Computes the tumor volume in the 3D object.*
   - ***3D Reconstruction**:*
     - *Generates 3D mesh from multi-Slice along with their masks*

C. Presentation Layer

1) *User interaction and visualization interface.*
- **Input**: Raw MRI image (uploaded by user).
- **Outputs**:
  - **Brain Tumor Classification**: Displays tumor type/confidence score.
  - **Size of Tumor**: Shows metrics (e.g., "Volume: 120 mm³").
  - **3D Visualization**: 3D model of the tumor.

2) *Interconnections & Data Flow*
3) *User Upload:*
   - Presentation Layer → Data Layer (stores raw MRI).

a) Processing Pipeline:
   - Data Layer → Application Layer: Sends raw MRI for preprocessing.

b) Results Delivery:
   - Application Layer → Data Layer: Saves results (e.g., tumor mask, proportion, 3D object).
   - Data Layer → Presentation Layer: Retrieves results for display.

c) User Interaction:
   - Presentation Layer queries User Database for authentication and history.

V. METHODOLGY

A. Custom CNN Architecture

We designed a lightweight CNN model for brain tumor classification, comprising:

- **Feature Extraction Blocks**: Three convolutional blocks with progressive channel expansion:

	Input Channels	Output Channels	Kernel Size	Activation	Pooling
First Conv Layer	3	32	4	ReLU	3*3 Max Pooling
Second Conv Layer	32	64	4	ReLU	3*3 Max Pooling
Third Conv Layer	64	128	4	ReLU	3*3 Max Pooling

1) Classification Head:
   - Flattened feature maps fed into a dense layer with SoftMax activation function, outputting probabilities

B. Image Processing for Classification:

All input MRI images underwent the following standardized preprocessing pipeline to ensure consistency and enhance model generalization:

Tensor Conversion:
Images were converted to PyTorch tensors to enable GPU-accelerated processing.

Resizing:
Uniformly resized to 150×150 pixels using bilinear interpolation with **anti-aliasing** to preserve structural integrity during downsampling.

Brightness Augmentation:
Applied color jitter to randomly adjust brightness to 85–115% of original values, simulating clinical imaging variations.

Standardization:
Normalized pixel values using ImageNet statistics using

Standardized Pixel Equation.

C. Image Preprocessing For Segmentation:

All MRI scans and corresponding masks underwent the following preprocessing:

1) Channel Handling:
   - *Grayscale images were expanded to 3-channel format for compatibility with pretrained encoders.*

2) Resizing:
   - *Uniformly resized to 256×256 pixels using bilinear interpolation to maintain aspect ratio.*

3) Normalization:
   - *Pixel values scaled to [0, 1] range*
   - Standardized using mean=0.0, std=1.0.

4) Mask Processing:
   - Converted to binary format (0=background, 1=tumor) for segmentation tasks.

5) Tensor Conversion:
   - Transformed to PyTorch tensors via ToTensorV2.

D. Data Augmentation Strategy for Segmentation

Applied **only during training** to increase dataset diversity:

Augmentation	**Parameters**
Rotation & Resizing	Random rotations (±15°), scale (0.9–1.1)
Flipping	Vertical/Horizontal (p=0.5)
Intensity Variation	Brightness/Contrast (±15%)
Noise Injection	Gaussian noise (σ=0.05)

VI. RESULTS

A. Equations

1) Cross-Entropy Loss for Classification:

Used to train the CNN classifier:

$$LCE = -\sum_{i=1}^{c} y(i) * \log\left(Y(i)\right) \tag{1}$$

where

- C is the number of classes.
- y(i) is the true label.
- Y(i) is the predicted probability for class i.

2) Dice Loss for Segmentation:

A common loss for tumor segmentation:

$$Dice = \frac{2 * |P \cap G|}{|P| + |G|} \tag{2}$$

where

- P is the predicted mask.
- G is the ground truth mask.

3) Intersection over Union (IoU):

$$iou = \frac{intersection}{union} \tag{3}$$

4) Tumor Proportion:

$$Tumor\ Proportion = \frac{Ntumor}{W * H} \tag{4}$$

where

- Ntumor is the number of white pixels
- W, H are the image width and height.

5) Precision:

$$\frac{TP}{TP + FP} \qquad (5)$$

6) Recall:

$$\frac{TP}{FN + TP} \qquad (6)$$

7) F1-Score
:

$$\frac{2.Precision.Recall}{Precision + Recall} \qquad (7)$$

8) Standardized Pixel:

$$\frac{Original\ Pixel - \mu}{\sigma} \qquad (8)$$

where μ = [0.485,0.456,0.406] and σ = [0.229,0.224,0.225]

B. Figures and Tables:

SEGMENTATION (FIG 1)

Model	**Metrics**			
	Val Dice	***Val IOU***	***Test Dice***	***Test IOU***
Deeplb v3_Reet101	82.73	70.83	83.4	71.38
Segformer1	83.32	73.59	84.05	74.08
Resnet 152	83.62	72.06	82.47	74.09
DynUnet	87.54	77.95	86.53	78.93
Attention Unet (1M Parameter)	86.47	76.34	86.95	79.47

Dice and IoU scores for segmentation are shown on both the kaggle Nikhil Tomar validation set (Val) and a kaggle Atika Akter11 and sabir ahmed test set (Test).

Fig. 1. Comparison of segmentation performance across various deep learning models using validation and test sets. Metrics reported include Dice Coefficient and Intersection over Union (IoU). The Attention UNet and DynUNet models show superior performance across most metrics.

CLASSIFICATION (FIG 2)

Model	**Metrics**			
	Training Accuracy	***Validation Accuracy***	***Testing Accuracy***	***Testing F1-score***
VGG16	27.92	30.87	30.89	47
MLP Mixer b16	91.71	91.23	91.23	90.75
Resnet50	97.71	96.04	96.03	96
Densenet 121	97.57	98.17	98.17	98.5
CNN from scratch	99.23	98.32	98.32	98.32

Fig. 2. Performance comparison of different classification models in terms of training, validation, and testing accuracy, along with testing F1-score. The custom CNN model achieved the highest overall performance.

CLASSIFICATION ACCURACY (FIG 3)

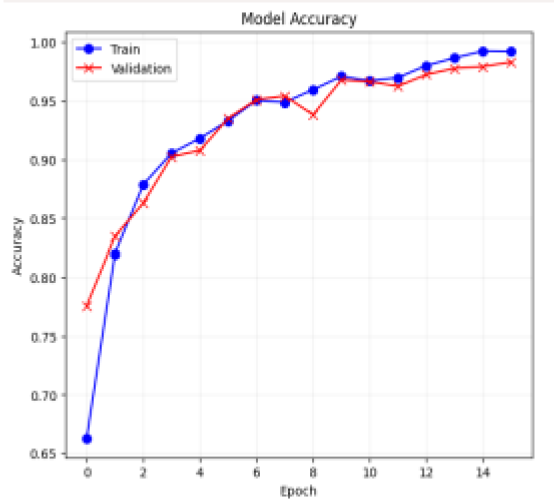


Fig. 3. shows a strong learning curve, with both training and validation accuracy steadily increasing and stabilizing above 97% by epoch 10, indicating excellent generalization performance.

CLASSICATION LOSS (FIG 4)

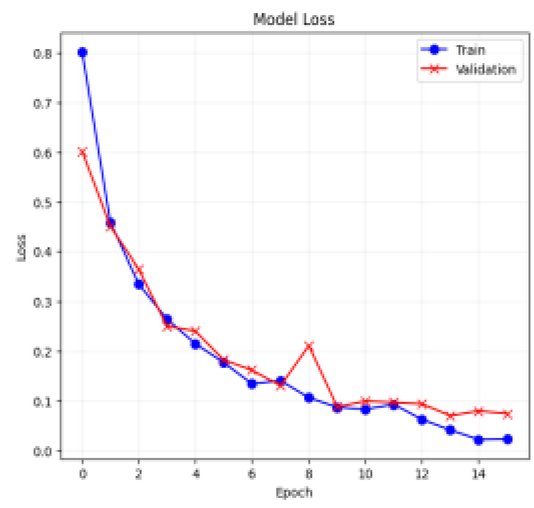


Fig. 4. The training and validation loss both show a steady decline across epochs, reaching below 0.1.This indicates good model performance with minimal overfitting or variance.

SEGMENTATION OUTPUT (FIG 5)

Fig. 5. compares the ground truth mask and predicted mask against the original input image for segmentation output evaluation.

VII. DATASET

A. *Segmentation:*

Class	Training & Validation Images	Test Images
Glioma	1426	619
Meningioma	708	969
Pituitary	930	964

The dataset is divided into two main subsets for machine learning purposes:

1. **Training & Validation Set (3,064 images) [9]**
   - Training: 80% (2,451 images)
   - Validation: 20% (613 images)
   - Used for model development and hyperparameter tuning
2. **Test Set (2552 images) [10]**
   - Represents unseen data to assess real-world performance.
   - Data was combined from classes 1,2,3.

B. *Classification:*

The dataset was partitioned into training/validation and testing sets with near-identical class distribution preservation:

Class	Training & Validation Images	Test Images
Glioma	1321	300
Meningioma	1339	306
Pituitary	1457	300
No Tumor	1595	405

VIII. CONCLUSION

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, 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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