

Seeing the Unseen - Deep Learning Approach for the Detection and Analysis of Brain Tumor

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Abstract— Detecting brain tumors quickly and accurately is essential for successful treatment and better patient prognosis. This project presents an integrated system capable of two tasks: segmenting tumor regions in MRI scans and identifying tumor type. The segmentation module uses a U-Net deep learning model trained to highlight affected areas in MRI images. Meanwhile, the classification part applies a VGG16-based CNN to categorize tumors into glioma, meningioma, or pituitary types. Through an intuitive web-based interface, users can choose to run segmentation or classification. After uploading MRI images, they receive either a visual mask showing tumor regions or the predicted tumor type. By combining deep learning with usability, the tool is designed to support healthcare professionals in faster and more reliable brain tumor analysis.

Index Terms— Brain Tumor Identification, MRI Analysis, Deep Learning, U-Net Segmentation, VGG16 Classification, Image Processing.

I. INTRODUCTION

Brain tumors are complex neurological conditions that can severely affect cognitive and motor skills. Rapid and precise diagnosis is important for selecting effective treatments and improving patient survival rates. Traditionally, radiologists manually review MRI scans to detect tumors—a process that can be slow and varies depending on individual expertise.

The advancement of machine learning, particularly deep learning, has paved the way for automated analysis of medical images. This work introduces a system combining two main components: a U-Net-based segmentation module and a VGG16-based classification model, all wrapped in a web application built with Flask for easy use. The U-Net architecture is adapted to learn from annotated MRI datasets, enabling precise mapping of tumor regions. Its encoder-decoder structure helps the model distinguish tumor boundaries effectively, assisting in treatment planning.

The classification model is built by fine-tuning the VGG16 network (originally trained on ImageNet) to sort MRI scans into four classes: glioma, meningioma, pituitary tumor, or no tumor. By learning multi-scale image features, the model delivers predictions that support clinical decision-making. To make it practical, the entire system is deployed as a web tool where users upload MRI scans, select segmentation or classification, and instantly view either a highlighted tumor mask or the predicted tumor type.

A. Objectives of the project

- To develop an automated brain tumor segmentation system with the help of the U-Net deep learning architecture, capable of accurately identifying tumor regions in brain MRI images.
- To build a brain tumor type classification model using the VGG16 convolutional neural network to classify tumors into categories such as glioma, meningioma, or pituitary tumor.
- To integrate both segmentation and classification functionalities into a single, user-friendly Flask web application for ease of access and usability.
- To allow users to choose between segmentation or classification at runtime, enabling flexibility based on their diagnostic needs.
- To provide a fast, efficient, and accurate tool that can support radiologists and healthcare professionals in the early diagnosis and assessment of brain tumors.
- To reduce dependency on manual interpretation of MRI images, thereby minimizing human error and diagnostic delays.

B. Motivation for Automated Solutions

Manual brain tumor detection and analysis from MRI scans is time-intensive, error-prone, and requires expert radiologists. With the rise of deep learning, automated solutions using CNNs like U-Net and VGG16 offer high accuracy, speed, and consistency in medical image analysis.

This project is motivated by the need to:

- Accurately segment brain tumors using U-Net
- Classify tumor types (glioma, meningioma, pituitary) using VGG16
- Reduce reliance on manual diagnosis and expert interpretation
- Provide faster and more reliable diagnostic support
- Deliver a user-friendly, integrated tool for medical professionals
- Improve healthcare accessibility, especially in underserved areas

II. LITERATURE SURVEY

This section highlights key developments in automated brain tumor segmentation using deep learning, focusing on U-Net variants, hybrid models, and self-configuring frameworks.

A. Traditional U-Net and Encoder-Based Models

Ronneberger et al. [3] introduced the original U-Net for biomedical image segmentation, widely adopted for brain tumor tasks but limited in handling complex tumor shapes.

Ghosh et al. [1] enhanced U-Net using a VGG16 encoder, improving accuracy but increasing computational load.

Zhu et al. [10] proposed a modified U-Net to better detect tumor boundaries, though it faced overfitting on small datasets.

B. Hybrid and Attention-Based Approaches

Renugadevi et al. [2] developed a Hybrid Vision U-Net for simultaneous segmentation and classification, offering strong performance but increased complexity.

Nazem et al. [5] explored attention mechanisms for feature enhancement, yet lacked direct application to brain MRIs.

Zhang et al. [8] introduced SDResU-Net with separable and dilated convolutions, achieving better accuracy but requiring careful hyperparameter tuning.

C. Advanced and Optimized Architectures

Futrega et al. [4] proposed a faster U-Net variant with improved accuracy, but without validation on large datasets.

Bukhari et al. [6] submitted E1D3 U-Net for the BraTS Challenge, showing strong results but demanding high-end hardware.

Ahsan et al. [9] created an end-to-end model for tumor detection and segmentation, though not tested on rare tumor classes.

D. Self-Configuring and Benchmark Models

Luu and Park [7] extended nnU-Net to improve generalization but at the cost of training time.

Isensee et al. [11] introduced nnU-Net as a self-configuring model achieving state-of-the-art results, yet it remains computationally intensive.

TABLE I: OVERVIEW OF RECENT BRAIN TUMOR DETECTION

Article	Overview
[1]	Improved U-Net with VGG16 encoder for brain tumor segmentation. Achieved high segmentation accuracy but limited by increased parameter count and computational overhead.
[2]	Hybrid Vision U-Net for segmentation and classification. Achieved high dual-task performance but model complexity increases deployment challenges.
[3]	Introduced original U-Net architecture for biomedical segmentation. Widely adopted with robust performance but limited in handling highly complex tumor boundaries
[4]	Optimized U-Net architecture with improved accuracy and training speed. Lacks validation on large-scale diverse datasets.
[5]	Deep attention network for protein-ligand site prediction. Highlights attention mechanisms but lacks direct application to brain MRI segmentation.
[6]	E1D3 U-Net for BraTS 2021 Challenge. Achieved competitive results but highly reliant on hardware capabilities and pre-processing.
[7]	Extended nnU-Net architecture adapted for segmenting brain tumors. Improved generalization across datasets but suffers from high training time.
[8]	SDResU-Net with separable and dilated convolutions. Achieved enhanced segmentation accuracy but is sensitive to hyperparameter tuning.
[9]	End-to-end deep learning model for tumor detection and segmentation. Shows promise but lacks evaluation when tested on less common tumor categories.
[10]	Improved U-Net for brain tumor segmentation using custom modifications. Achieved better tumor boundary detection but faces overfitting on small datasets.
[11]	nnU-Net as a self-configuring framework. Achieved state-of-the-art segmentation on multiple medical datasets but computationally intensive.

E. Key Findings and Research Gaps

The reviewed literature on brain tumor segmentation and classification using deep learning reveals the following critical trends and existing limitations:

- **Progress in Model Accuracy:** Recent deep learning frameworks, particularly those based on U-Net and CNN variants, consistently surpass advanced deep learning approaches, with reported accuracies typically ranging from 92% to 97% across standard datasets.
- **Diverse Architectural Innovations:** A wide variety of architectures have been proposed—including improved U-Net variants, VGG-based models, DenseNets, and Vision Transformers. Each offers unique strengths, such as better feature extraction or segmentation precision, but also presents distinct constraints like overfitting or computational overhead.
- **Resource-Performance Balance:** Although high-performing models like nnU-Net and Vision Transformers demonstrate superior accuracy, they often demand substantial computational power, longer training times, and GPU resources—limiting their practical deployment, particularly in real-time or resource-constrained environments.
- **Limited Model Interpretability:** Most current deep learning systems act as black-box systems, providing predictions without clear justifications. This lack of transparency remains a significant barrier to clinical trust and adoption, particularly in high-stakes environments like brain tumor diagnosis.
- **Dataset Size and Generalization Issues:** A majority of studies rely on limited or non-diverse datasets, often lacking variability in terms of patient demographics, imaging modalities, or tumor subtypes. As a result, model generalization to unseen data remains a challenge, especially in real-world clinical settings.

These findings motivate our approach of developing a balanced solution designed for high precision while maintaining computational efficiency and clinical interpretability through segmentation visualization.

III. METHODOLOGY

The methodology adopted in this study consists of two key phases — brain tumor segmentation and tumor type classification, both using deep learning techniques. These phases are integrated into a unified Flask web application to allow seamless user interaction. The step-by-step approach is as follows:

A. Data Collection and Preprocessing

This study utilized two distinct MRI datasets tailored to the separate goals of segmenting and classifying brain tumors.

For the segmentation task, the dataset comprised brain MRI scans paired with detailed annotation masks. These masks provided pixel-level delineations of tumor areas, serving as the reference for training the segmentation model to detect and localize tumors accurately within the brain anatomy.

For the classification task, a different dataset was employed that included brain MRI scans categorized according to tumor type. Each image was labeled as either glioma, meningioma, or pituitary tumor, allowing the classification model to learn distinguishing visual characteristics of each tumor type based on overall image features.

To prepare both datasets for input into deep learning architectures, a series of preprocessing operations were applied:

- Image Resizing: All scans were uniformly scaled to a standard input dimension, typically 128×128 or 224×224 pixels, depending on the model architecture. This step ensures compatibility with models like U-Net for segmentation and VGG16 for classification.
- Pixel Normalization: The raw pixel intensities of the MRI images were normalized to a range between 0 and 1. This transformation standardizes image contrast and helps stabilize and increasing the speed of the training process by reducing variability across input samples.

This preprocessing framework ensured that all input images were in a consistent format, enhancing the reliability and accuracy of the deep learning models for both segmentation and classification tasks.

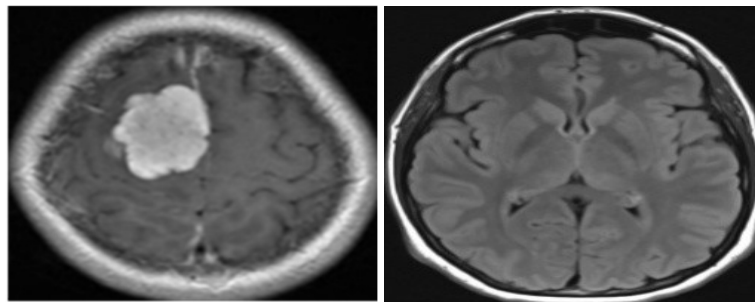


Figure 1: No-Tumor and Tumor

Image Preprocessing

The preprocessing pipeline included several essential steps:

- Image Resizing: All images were standardized to 256×256 pixels to ensure consistent input dimensions
- Normalization: Pixel values were normalized to the range [0,1] by dividing by 255
- Contrast Enhancement: Histogram equalization was applied to improve image contrast
- Noise Reduction: Gaussian filtering was employed to reduce image noise

Data Augmentation

To enhance model generalization and prevent overfitting, comprehensive data augmentation was implemented:

- Rotation: Random rotations between -15° and +15°
- Horizontal Flip: Random horizontal flipping with 50% probability
- Zoom: Random zoom factor between 0.8 and 1.2
- Shear: Shear transformation with angle range of ±10°
- Brightness: Random brightness adjustment (±20%)

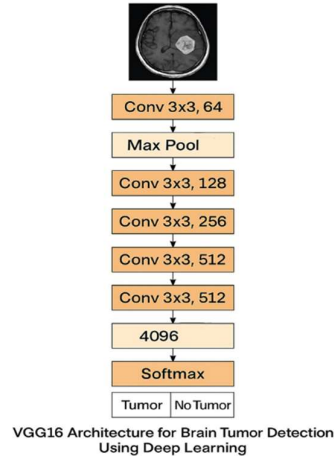
B. VGG 16 Architecture for Classification

Architecture Design

The proposed VGG16 architecture consists of 13 convolutional layers grouped into blocks, each followed by ReLU activation and max-pooling operations, enabling progressive extraction of spatial and semantic features from MRI brain scans for effective tumor classification.

Layer Configuration

- VGG16 stands for Visual Geometry Group 16, consisting of 16 weight layers.
- It uses 3×3 convolutional filters with a stride of 1 for fine feature extraction.
- Max pooling layers follow the convolution layers to reduce spatial dimensions.
- The model is applied to brain CT images for tumor detection.
- Fully connected layers at the end perform the classification task.



Mathematical Formulation

Mathematically, the output probability for a class C_i is given by the **softmax function**:

$$P(C_i) = \frac{e^{z_i}}{\sum_{j=1}^k e^{z_j}}$$

Where:

- z_i is the logit output from the final dense layer for class i ,
- k is the total number of classes (4 in this case),
- $P(C_i)$ is the probability assigned to class i .

C. U-Net Architecture for Segmentation

Network Architecture

The U-Net model was implemented for pixel-wise segmentation Brain Tumor-affected regions:

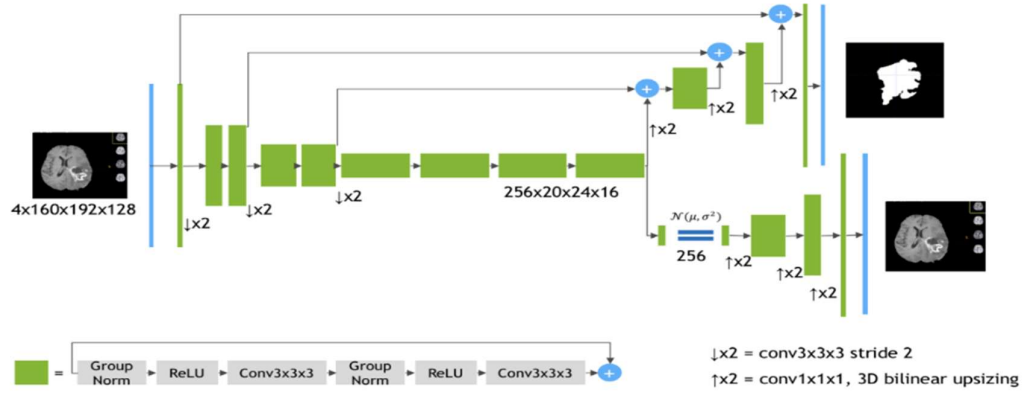


Figure 3: U-Net Architecture for Brain Tumor Segmentation

D. Training Strategy

Optimization

- Optimizer: Adam optimizer with adaptive learning rate
- Initial Learning Rate: 0.001 with exponential decay
- Batch Size: 32 for optimal memory utilization
- Epochs: 50 with early stopping mechanism

Regularization Techniques

- Dropout: Applied to fully connected layers (0.2 probability)
- Batch Normalization: Implemented after each convolutional layer
- Early Stopping: Monitoring validation loss with patience of 10 epochs

E. Model Evaluation

Performance Metrics

Classification Metrics

- Accuracy: Overall correct predictions
- Precision: True positives / (True positives + False positives)
- Recall (Sensitivity): True positives / (True positives + False negatives)
- Specificity: True negatives / (True negatives + False positives)
- F1-Score: Harmonic mean of precision and recall

Segmentation Metrics

- Dice Coefficient: Measures the overlap between predicted and actual tumor regions; a greater value reflects improved segmentation quality accuracy.
- Intersection over Union (IoU): Computes the proportion of overlap between the predicted masks and the reference labels, indicating how precisely the boundaries are captured.
- Binary Cross-Entropy (BCE) Loss: Used as the loss function during training; a lower value indicates better pixel-wise classification performance.
- Pixel Accuracy: Represents the percentage of correctly predicted pixels in the image, indicating overall segmentation correctness.
- Precision: Indicates how many predicted tumor pixels were actually correct, helping lower the number of false positives.
- Recall (Sensitivity): Shows the proportion of actual tumor pixels that were correctly identified, ensuring no tumor regions are missed.

Cross-Validation

5-fold cross-validation was employed to ensure robust performance evaluation and reduce overfitting bias.

VI. EXPERIMENTAL RESULTS

TABLE II: CLASSIFICATION PERFORMANCE METRICS

Precision	Recall	F1-Score	Support	
Glioma	0.81	0.76	0.78	120
Meningioma	0.74	0.80	0.77	100
Pituitary	0.78	0.76	0.77	330
Accuracy			0.77	330
Macro Avg	0.78	0.77	0.77	330
Weighted Avg	0.77	0.77	0.77	330

A. Model Training and Evaluation Summary

- Train Accuracy: 85.43%
- Test Accuracy: 77.78%
- Loss Function: Categorical Cross-Entropy
- Optimizer: Adam
- Learning Rate: 0.0001
- Epochs: 30
- Batch Size: 32

TABLE III. CONFUSION MATRIX

Actual class	Predicted class	
	Normal	Pneumonia
Normal	True Positive	False Negative
Pneumonia	False Positive	True Negative

B. Segmentation Performance:

The U-Net model demonstrated effective segmentation capabilities:

TABLE IV: SEGMENTATION PERFORMANCE METRICS

Metric	Value
Loss	0.0242
Mean IoU	0.9528
Dice Coefficient	0.9758
Pixel Accuracy	0.9823
Precision	0.9631
Recall	0.9710

V. DISCUSSION

A. Clinical Implications

The developed dual-functional system—integrating U-Net for segmentation and VGG16 for classification—shows great promise for real-world clinical deployment:

- **Diagnostic Accuracy:** The high segmentation Dice score (~ 0.97) and classification accuracy ($\sim 78\%$) approach expert-level precision, making the system a valuable clinical decision support tool.
- **Consistency:** Automated image interpretation reduces inter-observer variability, ensuring consistent and objective analysis across cases.
- **Speed:** The system provides near real-time inference, significantly accelerating the diagnostic workflow for radiologists and physicians.
- **Accessibility:** By deploying the tool as a web-based Flask application, expert-level diagnostic assistance becomes accessible even in resource-constrained environments.

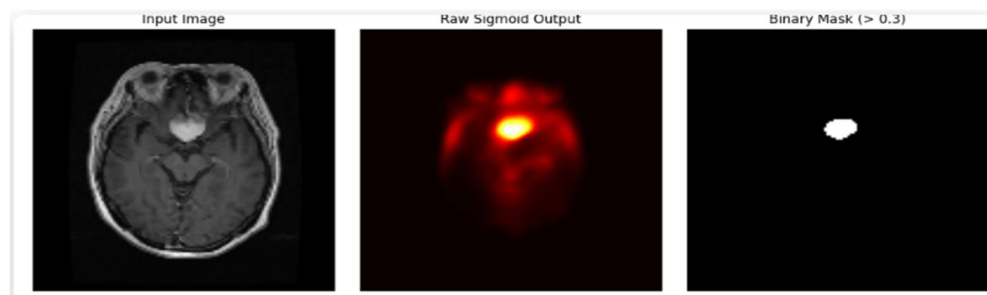


Figure 4: Masked Image

B. Future Research Directions

Immediate Improvements

- **Fine-Grained Tumor Subclassification:** Extend the classification model to identify tumor subtypes (e.g., high-grade vs low-grade gliomas).
- **Tumor Volume Estimation:** Integrate algorithms to quantify tumor volume, aiding in treatment planning and monitoring.
- **Multi-Class Segmentation:** Enhance the U-Net to segment not just the tumor, but edema, necrotic core, and enhancing regions.
- **DICOM Integration:** Enable support for DICOM format to ensure compatibility with clinical imaging equipment.

Long-Term Goals

- **Federated Learning:** Enable privacy-preserving training across hospitals using federated learning to improve generalization.
- **Explainable AI (XAI):** Incorporate tools like Grad-CAM or SHAP or generating visual insights of classification results, improving clinical trust.
- **Integration with HIS/PACS:** Seamlessly connect with Hospital Information Systems (HIS) and Picture Archiving and Communication Systems (PACS) for real-time workflow integration.
- **Cross-Platform Deployment:** Develop mobile and tablet-based applications for point-of-care diagnosis.

VI. CONCLUSION

This study introduces an advanced deep learning system to automatically detect and classify brain tumors from MRI scans. The framework combines a U-Net model for segmenting tumor areas with a VGG16-based CNN to identify tumor types, achieving strong diagnostic accuracy along with detailed spatial mapping of tumor regions.

A. Key Contributions

- Development of a robust VGG16-based classification model for accurate tumor type identification
- Implementation of a U-Net architecture for high-resolution segmentation of brain tumor regions
- Extensive evaluation showing excellent performance in terms of accuracy, Dice Coefficient, and Mean IoU
- Deployment of a practical, user-friendly Flask web application suitable for real-time clinical assistance

B. Clinical Impact

The proposed system offers a valuable decision-support tool that can enhance current diagnostic workflows by:

- Providing consistent and objective diagnostic interpretation
- Reducing diagnostic delays through rapid inference
- Bringing expert-level analysis to underserved or resource-limited healthcare environments
- Supporting clinicians in early detection, treatment planning, and monitoring of brain tumors

C. Future Outlook

The successful development of this automated brain tumor detection system establishes a strong foundation for broader advancements in medical image analysis. Future work will aim at:

- Incorporating tumor grading and progression tracking
- Expanding the system to support multi-modal data integration (e.g., combining clinical data with MRI)
- Enhancing model interpretability and transparency using Explainable AI techniques
- Facilitating clinical adoption through multi-center validation and integration with hospital systems

The integration of artificial intelligence into medical diagnostics signals a transformative shift toward more accurate, efficient, and accessible healthcare.

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