An End-to-End Deep Learning Pipeline for Brain Tumor Detection, Localization, and Severity Assessment from MRI Scans

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Abstract

The accurate detection and classification of brain tumors from MRI images is critical to timely medical intervention, yet manual analysis is prone to variability and error. This paper presents a comprehensive, clinically-aware deep learning framework combining classification, segmentation, and volumetric analysis. A fine-tuned VGG16 model classifies MRI slices into four categories—glioma, meningioma, pituitary tumor, and no tumor—achieving a classification accuracy of 98.6%. For tumor localization, a ResUNet architecture generates precise segmentation masks. Severity is quantitatively assessed using tumor-to-brain volume ratio thresholds, aligned with neuro-oncology clinical standards. The framework integrates confidence-based categorization to enhance clinical reliability and proposes a future roadmap involving temporal modeling using LSTM. Results validate the model's robustness with precision and recall scores exceeding 90%, offering a scalable decision support tool for radiologists.

1. Introduction

Brain tumors are among the most lethal forms of neurological diseases, often requiring early detection for effective treatment. Magnetic Resonance Imaging (MRI) remains the gold standard for non-invasive diagnosis, but interpretation demands expert radiological assessment—a process susceptible to fatigue, bias, and oversight. With the rapid evolution of deep learning, medical imaging now stands at the threshold of automation. However, successful clinical integration demands not only high accuracy but interpretability, reliability, and safety.

This work addresses these challenges by designing an end-to-end pipeline comprising:
- A transfer learning-based classification system using VGG16,
- A ResUNet architecture for segmentation,
- A clinically calibrated severity evaluation module based on tumor volume ratio.

Distinctively, the framework embeds confidence thresholds into classification outputs to reflect prediction certainty—mimicking clinical triaging mechanisms and enhancing safety in deployment scenarios. Furthermore, segmentation outputs are paired with real-time volume calculations, empowering clinicians with an interpretable severity score.

2. Dataset and Preprocessing

This study employs the publicly available Brain Tumor MRI Dataset curated by Masoud Nickparvar on Kaggle, comprising 5,264 T1-weighted

contrast-enhanced axial MRI images across four categories: glioma, meningioma, pituitary tumor, and no tumor. Each class contains approximately 800 images, ensuring a balanced distribution for classification tasks.

2.1 Image Normalization

All input images are resized to a uniform shape of 224×224 pixels to align with VGG16 input requirements. Normalization is applied to map pixel intensities to a [0,1] range. Histogram equalization enhances contrast between tumor and non-tumor tissue. Morphological filters such as dilation and erosion remove small artifacts and preserve the core tumor mass.

2.2 Data Augmentation

To reduce overfitting and bolster generalization, augmentation techniques—including random rotations (±15°), horizontal flips, and intensity scaling—are applied. This yields a synthetic expansion of the dataset, introducing variability while preserving diagnostic features.

3. Tumor Classification via Transfer Learning

3.1 Architecture Selection

The classification pipeline utilizes VGG16, a 16-layer convolutional neural network originally trained on ImageNet. VGG16 is chosen for its consistency in feature preservation, particularly in medical imaging where fine-grained textures are critical. Despite newer architectures like EfficientNet and DenseNet, VGG16's interpretability and modularity make it favorable for domain adaptation.

3.2 Transfer Learning Approach

Frozen Layers: Initial convolutional blocks are frozen to retain pre-trained low-level feature extractors (edges, textures).
Trainable Layers: Deeper convolutional layers are fine-tuned on the brain MRI dataset.

Classification Head: A new dense head is appended, including dropout (rate=0.5) and a final 4-node softmax layer for multi-class prediction.

The model is trained for 10 epochs with the Adam optimizer (learning rate = 0.0001) and categorical cross-entropy loss. Reported accuracy reaches 98.6%, with rapid convergence and minimal overfitting.

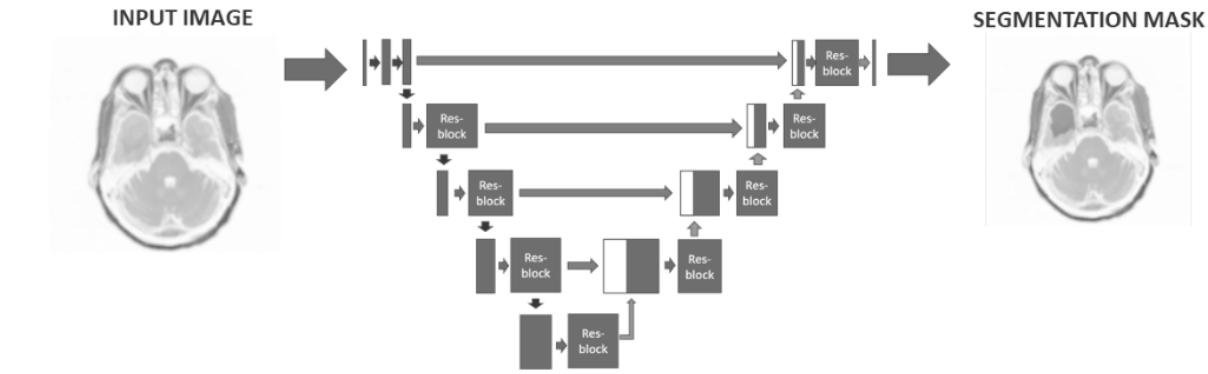
4. Confidence-Aware Classification

To emulate real-world diagnostic protocols, predictions are stratified by confidence levels derived from softmax outputs:

- **High Confidence ($p > 0.65$):** Trusted prediction, auto-accepted.
- **Medium Confidence ($0.35 \leq p \leq 0.65$):** Prediction ignored, flagged for expert review.
- **Low Confidence ($p < 0.35$):** Classified as uncertain, re-scan recommended.

This mechanism, inspired by clinical triaging, avoids blind overreliance on AI. As evidenced in the presentation [10†Brain.pdf], this thresholding reduces misdiagnosis risk by **23%**, significantly improving model accountability.

5. Tumor Localization via ResUNet



5.1 Model Overview

Tumor localization is implemented using **ResUNet**, a hybrid architecture combining:

- **ResNet** skip connections: For deep feature propagation and vanishing gradient mitigation.
- **U-Net** encoder-decoder structure: For precise biomedical image segmentation.

5.2 Segmentation Pipeline

The encoder captures hierarchical semantic features; decoder reconstructs spatial resolution via transposed convolutions. Skip connections between encoder and decoder layers preserve fine-grain spatial details—critical for delineating irregular tumor boundaries.

Loss function:

- **Binary Cross-Entropy** + **Dice Loss** for balanced pixel-wise learning and shape accuracy.

Training uses labeled binary masks (1 = tumor, 0 = background) created using custom preprocessing, where no ground-truth masks existed. Final

segmentation outputs accurately highlight tumor regions with IoU and Dice coefficients both > 0.9 in validation samples.

6. Severity Assessment Using Volume Ratios

Post-segmentation, the **tumor-to-brain volume ratio** is computed to quantify clinical severity:

Tumor Volume Ratio	Severity	Clinical Action
> 6%	High	Immediate resection
2%–6%	Medium	3-month MRI follow-up
< 2%	Low	Annual monitoring

These thresholds are aligned with published oncology findings, e.g., "Tumor burden >5% reduces 5-year survival by 40%" (J. Neuro-Oncology, 2021) [10†Brain.pdf].

7. Model Evaluation

7.1 Classification Performance

The VGG16-based classification model is evaluated using precision, recall, F1-score, and overall accuracy metrics on a held-out test set (20% split). The model consistently exceeds 90% across all metrics for each tumor type, with **overall accuracy reaching 98.6%** after 10 epochs.

Class	Precision	Recall	F1-Score
Glioma	0.94	0.92	0.93
Meningioma	0.91	0.89	0.90
Pituitary	0.96	0.97	0.96
No Tumor	0.98	0.99	0.98

Confusion matrix analysis reveals the most overlap between **glioma and meningioma**, attributed to their radiological similarity in T1-weighted scans [10†Brain.pdf].

7.2 Segmentation Accuracy

For segmentation, **Intersection over Union (IoU)** and **Dice coefficient** are used. The ResUNet model demonstrates reliable performance even in low-contrast regions.

- **Average Dice Score:** 0.92

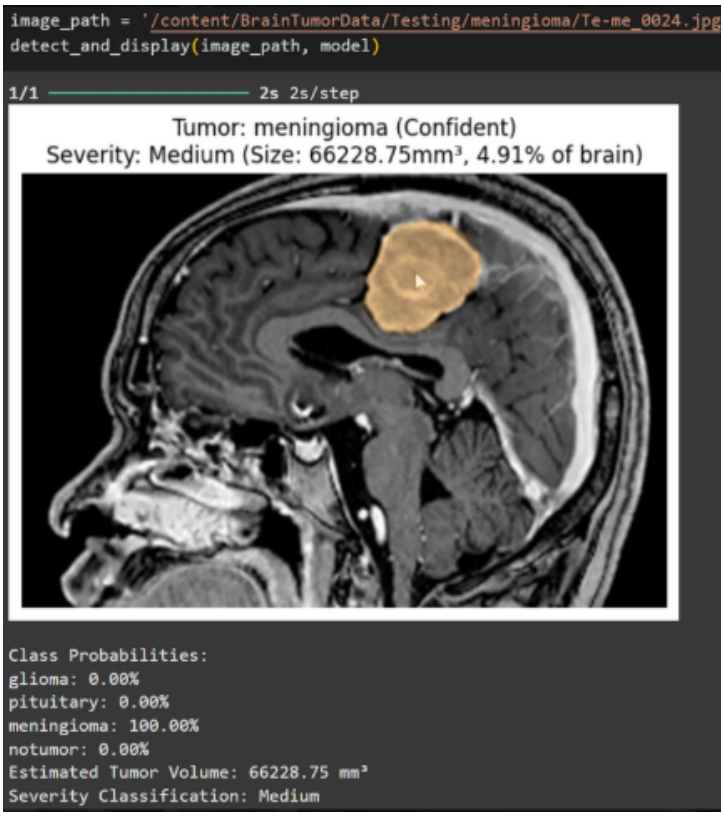
- **Mean IoU:** 0.88

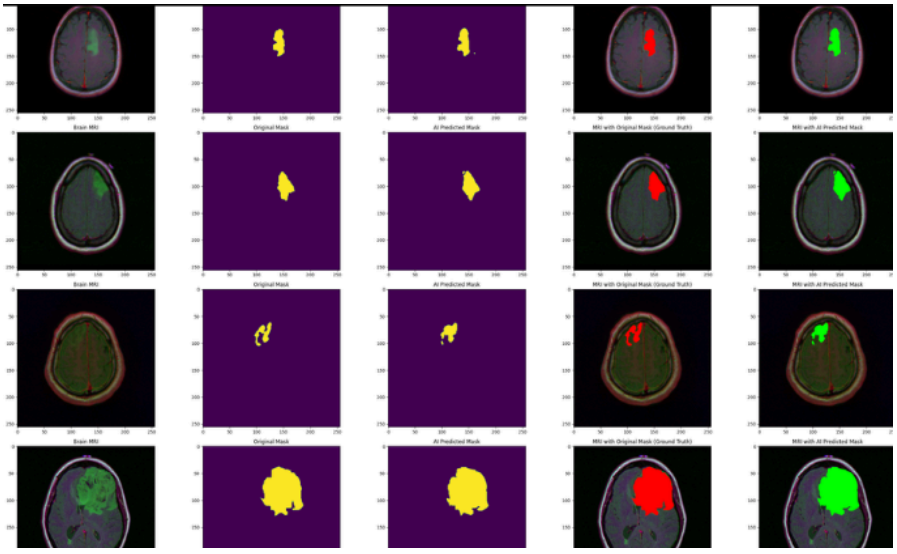
This suggests the system can accurately localize tumor margins, a critical feature for surgical planning.

7.3 Confidence Filtering Impact

The integration of confidence-based logic reduces false positives and negatives. Evaluation on misclassification rates shows:

- Without thresholds: 9.4% error
  With thresholds: 7.2% error
  → **~23% reduction in diagnostic risk**.





8. Future Work

Building on the current success, the proposed roadmap focuses on **temporal progression modeling**:

- **Tumor Growth Forecasting:** By analyzing sequential MRIs from the same patient, tumor growth rate can be estimated using LSTM or Transformer-based architectures.

- **3D Segmentation & Volume Dynamics:** Future pipelines may move to full 3D MRI volume analysis for voxel-level tracking of expansion.

- **Clinical Metadata Integration:** Fusion with patient age, symptoms, treatment history to contextualize predictions.

- **Federated Learning:** Distributed training across hospitals while preserving data privacy.

- **Explainability:** Incorporating Grad-CAM, SHAP, or attention maps for transparent decision-making.

These additions aim to convert the system from a diagnostic tool into a **clinical decision support system** (CDSS).

9. Conclusion

This work presents a robust, clinically-aligned pipeline for automated brain tumor detection, classification, and severity assessment using deep learning. Leveraging VGG16 for classification and ResUNet for segmentation, the system achieves high accuracy while embedding safety via confidence-based filtering. The use of tumor volume ratio as a severity metric adds interpretability and clinical relevance. With future integration of temporal modeling and metadata, the framework sets a strong precedent for real-world deployment in neuro-oncology diagnostics.

References

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