NeuroShield: AI-Driven Brain Tumor Detection and Risk Assessment

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Abstract
Brain tumors are life-threatening conditions caused by the abnormal and uncontrolled growth of cells within the brain. Accurate and timely diagnosis is essential to improve treatment outcomes and increase patient survival rates. This study presents an advanced deep learning-based system for brain tumor diagnosis that integrates ResNet50 Convolutional Neural Networks (CNNs) with Swin Transformer V2-B architectures. The CNN captures fine-grained spatial features, while the Swin Transformer extracts global contextual information from MRI scans. A hybrid feature fusion strategy combines these strengths to enhance classification accuracy, distinguishing among glioma, meningioma, and pituitary tumors. In addition to classification, the system estimates key tumor characteristics—such as area, diameter, and perimeter (in millimeter)—categorizes tumors into size groups (Very Small to Very Large), and assesses associated risk levels. It also generates detailed clinical diagnostic reports to support medical professionals in decision-making. Trained on publicly available MRI datasets, the system demonstrates superior performance in terms of accuracy, sensitivity, and specificity compared to traditional machine learning methods. This automated diagnostic tool streamlines radiological workflows and supports consistent, reliable clinical evaluations, ultimately improving patient care and outcomes.

Keywords: Brain Tumor Diagnosis, Deep Learning, CNN, Swin Transformer, MRI Classification, Tumor Size Estimation, Risk Assessment.

1. Introduction

Brain tumors are abnormal cell growths within the brain that can interfere with essential neurological functions. These tumors may be benign (non-cancerous) or malignant (cancerous), with the latter often posing greater health risks. Common symptoms include headaches, seizures, and cognitive or motor impairments. Globally, brain tumors affect over 300,000 individuals annually. Among the most common types are gliomas, meningiomas, and pituitary tumors.

Accurate and timely diagnosis of brain tumors is crucial for selecting the most effective treatment and improving patient outcomes. MRI (Magnetic Resonance Imaging) is widely used for detecting and analyzing brain tumors, providing detailed insights into their structure and location. However, analyzing these images involves handling large volumes of complex data, which can be time-intensive and requires consistent evaluation methods. To address these challenges, deep learning techniques have been introduced to assist in tumor classification and segmentation. While existing models have achieved progress in identifying tumor regions, many do not integrate multiple key tasks-such as classification, size measurement, risk assessment-within a single system.

NeuroShield introduces a unified deep learning framework that combines ResNet50, a convolutional neural network, with Swin Transformer V2-B, a vision transformer model. This hybrid system classifies brain tumors into gliomas, meningiomas, and pituitary tumors, estimates tumor dimensions (area, diameter, and perimeter), categorizes tumor size, assesses associated risk levels, and automatically generates structured clinical reports. By combining multiple capabilities into one platform, this approach enhances diagnostic precision, supports treatment planning, and contributes to better healthcare outcomes.

2. Literature Survey

Brain tumor diagnosis using automated techniques has attracted significant research interest due to the potential for improving diagnostic accuracy and reducing workload on medical professionals. Various machine learning and deep learning methods have been proposed, leveraging MRI data to detect and classify brain tumors efficiently.

Muhammad Aamir et al. [1] proposed a hyperparameter-optimized Convolutional Neural Network (CNN) model that fine-tunes parameters such as batch size, learning rate, and filter size. Trained on multiple Kaggle datasets, the model achieved an impressive average accuracy of 97%, demonstrating its effectiveness in brain tumor detection and classification.

Ihtisham Ul Haq et al. [2] developed a machine vision-based multiclass classification approach combining AlexNet CNN for feature extraction with an ensemble classifier. This hybrid approach attained 96% accuracy and highlighted its potential for early, non-invasive brain tumor diagnosis, thereby reducing mortality risks.

Haitham Alsaif et al. [3] focused on improving detection accuracy through data augmentation techniques applied to CNN architectures like ResNet, AlexNet, and VGG. Their model successfully enhanced the performance of automated brain tumor diagnosis by optimizing deep learning strategies.

Manav Sharma et al. [4] utilized a CNN-based machine learning model for brain tumor detection and segmentation from MRI scans. Their method, evaluated on an online dataset, achieved a high accuracy of 97.79%, confirming the promise of CNNs in clinical applications.

Gauravkumar Ahire et al. [5] introduced an automated brain tumor detection framework combining CNNs with blockchain technology for MRI image classification. Their approach achieved 97.5% accuracy and emphasized the importance of computer-aided diagnosis for improving accuracy and reducing manual effort.

Sunil Kumar et al. [6] provided a comprehensive review of brain tumor detection techniques spanning two decades, highlighting challenges like image restoration and enhancement. Their study analyzed CNN-based classification methods implemented in Python and TensorFlow, offering valuable insights for future research to improve detection accuracy with minimal errors.

Angona Biswas and Md. Saiful Islam [7] proposed a hybrid classification system integrating K-means clustering for tumor segmentation and Artificial Neural Networks (ANN) for tumor classification. The system included preprocessing steps such as resizing and contrast enhancement, combined with feature extraction via discrete wavelet transform and dimensionality reduction using principal component analysis.

Anil Kumar Budati and Rajesh Babu Katta [8] presented a machine learning-based brain tumor detection method using Support Vector Machines (SVM) and K-Nearest Neighbors (KNN). Their approach involved preprocessing, segmentation through the Chan-Vese method, and feature extraction with Gray Level Co-occurrence Matrix (GLCM). Evaluated on the BRATS 2017 dataset, their model outperformed existing techniques with high accuracy.

3. Methodology

The development of the NeuroShield System involved integrating advanced deep learning models with efficient software tools to enable accurate and automated classification of brain tumors from MRI scans. The overall methodology encompassed technology selection, model development, system design, and deployment, as outlined below.

3.1 Technologies Used

- **PyTorch:** For implementing and training the hybrid model integrating ResNet50 CNN and Swin Transformer V2-B, enabling efficient GPU-based learning.
- **OpenCV:** To preprocess MRI images via resizing, normalization, and contrast enhancement.
- **Flask:** For backend web development, handling image uploads, predictions, and result delivery through a user-friendly interface.

3.2 Requirements Gathering:

Initial requirements were collected from clinical experts and technical stakeholders to define essential system features such as multi-class tumor classification (glioma, meningioma, pituitary tumors), tumor size estimation (area, diameter, perimeter), risk assessment, and automated report generation.

3.3 System Design:

A modular architecture was designed to integrate local spatial feature extraction through ResNet50 CNN with global contextual feature modelling via Swin Transformer V2-B. Key modules included MRI validation, preprocessing, hybrid model prediction, tumor measurement, risk evaluation, and PDF report generation.

3.4 Model Implementation and Training:

The hybrid model was implemented in PyTorch and trained on publicly available brain tumor MRI datasets. A feature fusion strategy combined outputs from both CNN and Transformer branches to enhance classification performance. Extensive hyperparameter tuning optimized accuracy and minimized overfitting.

3.5 Testing and Evaluation:

Functional manual testing ensured smooth operation from image upload through prediction and report generation, validating system behaviour across different tumor types and MRI qualities. Performance metrics such as accuracy, precision, recall, F1-score, and area under the ROC curve (AUC) were computed on separate test datasets to assess model robustness. The web interface underwent cross-browser testing on Chrome, Firefox, Edge, and Safari to verify compatibility and provide a consistent user experience. Additionally, inference speed and system responsiveness were measured under varying MRI image sizes to optimize processing time without compromising accuracy.

3.6 Deployment:

The web application was deployed using Flask on either local or cloud servers, enabling secure user uploads of MRI scans and real-time tumor classification with downloadable PDF reports. Post-deployment monitoring included system usage tracking, error logging, and server performance checks. Regular maintenance tasks involved model retraining with new data, software updates, and security audits to ensure long-term reliability.

4. System Design

4.1 System Architecture

The architecture of the NeuroShield: Brain Tumor Detection System is designed to facilitate a seamless diagnostic workflow from MRI upload to clinical report generation, leveraging hybrid deep learning techniques and a modular web-based interface. The system integrates multiple functional components that work together to ensure reliable, efficient, and user-centric brain tumor analysis.

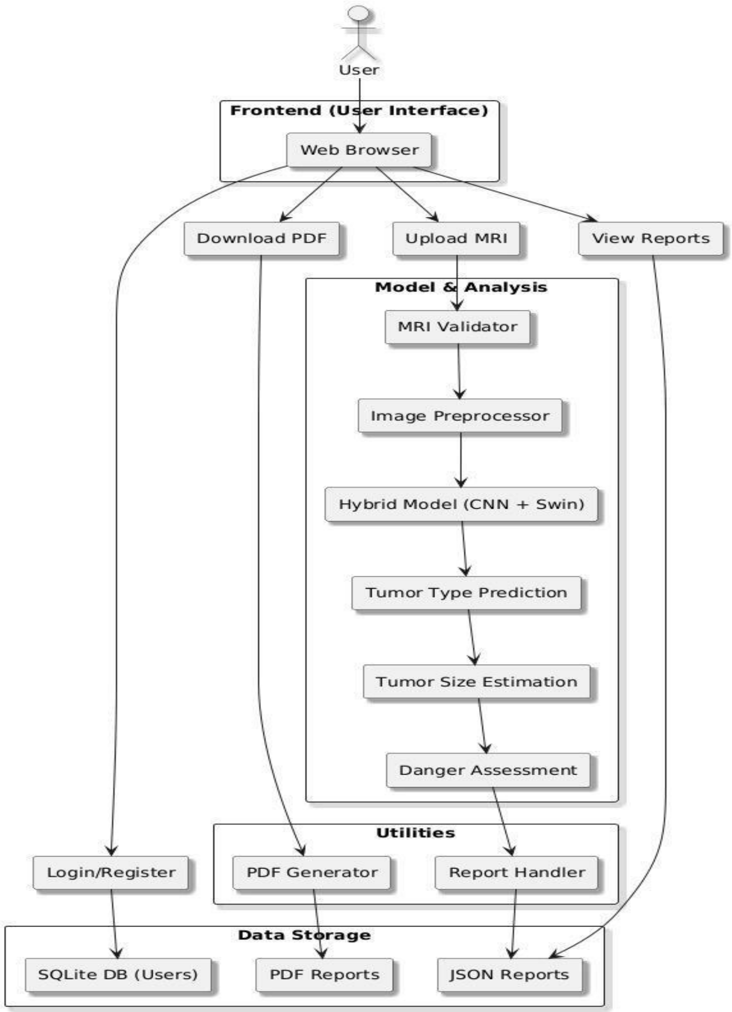

Figure 1: System Architecture of NeuroShield

As illustrated in Figure 1, the system architecture is divided into eight core modules, each responsible for specific operations within the diagnostic pipeline. It begins with a robust user authentication module leveraging SQLite for secure credential management, ensuring authorized access and data privacy. Upon login, users can upload MRI scans which undergo automatic validation to verify format correctness and image quality. Preprocessing standardizes the input through resizing, grayscale conversion, and intensity normalization to optimize model performance. The core analytical engine employs a hybrid deep learning model that combines ResNet50 CNN for local spatial feature extraction with Swin Transformer V2-B to capture long-range contextual information. Outputs from both networks are fused to enhance tumor classification accuracy across four categories: glioma, meningioma, pituitary tumor, and no tumor. For detected tumors, geometric measurements such as area, perimeter, and diameter are computed and used to categorize tumor size, which feeds into a clinical risk assessment assigning low, moderate, or high-risk levels. A comprehensive diagnostic report, including classification results, tumor metrics, risk level, confidence scores, and clinical recommendations, is generated in PDF format and stored securely alongside JSON metadata. The Flask-based web interface facilitates intuitive interaction, enabling users to upload scans, access detailed reports, and manage sessions securely. This modular, scalable architecture supports reliable tumor detection and characterization in both local and cloud environments.

4.2 Process Flow

The NeuroShield System follows a streamlined process beginning with secure user login. Users upload MRI scans and patient details via a web interface. The system validates the image, preprocesses it, and feeds it into a hybrid model combining ResNet50 CNN and Swin Transformer V2-B for tumor classification. If a tumor is detected, its size is estimated and a risk level is assigned. A detailed PDF report is then generated and made available for viewing or download. The overall workflow is illustrated in Figure 2.

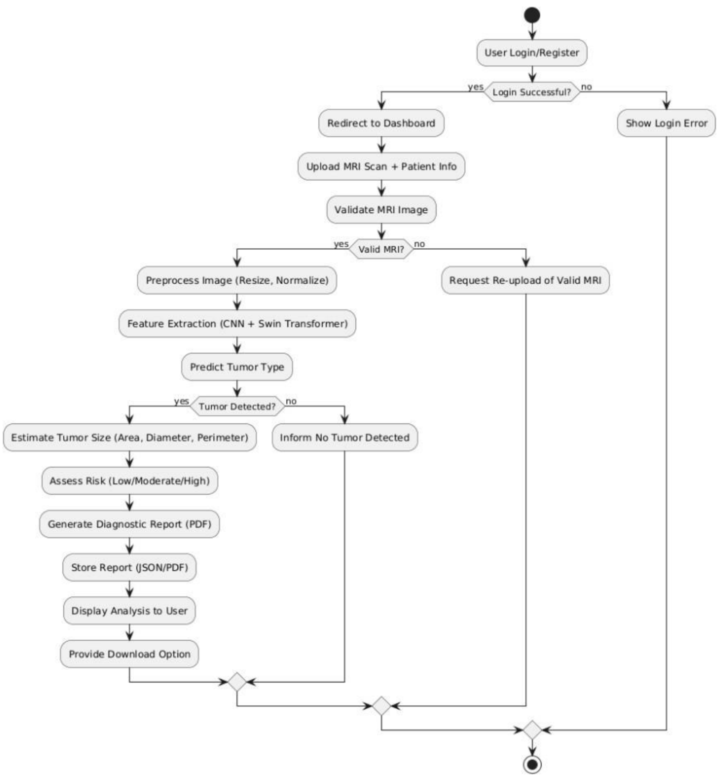

Figure 2: Process Flow Diagram of NeuroShield System

5. Implementation

This section outlines the core implementation aspects of the NeuroShield System, covering tools, model training, interface integration, execution requirements, and tumor size estimation formulas.

5.1 Tools and Technologies

- **Frontend:** HTML5 and CSS3 for structuring and styling web pages.
- **Backend:** Flask framework to manage routing, session handling, and server-side logic.

- **Deep Learning:** PyTorch for implementing the hybrid model combining ResNet50 CNN and Swin Transformer V2-B.
- **Image Processing:** OpenCV for MRI preprocessing—format validation, resizing (224×224 pixels), grayscale conversion, and normalization.
- **Database:** SQLite for lightweight user authentication and session management.
- **PDF Reports:** ReportLab and FPDF automate clinical report generation.
- **Environment:** Python 3.8+ with necessary ML libraries; GPU acceleration recommended.

5.2 Model Training and Evaluation

The hybrid model fuses local spatial features (ResNet50) and global contextual features (Swin Transformer). Both models were trained on labeled MRI datasets, with outputs concatenated and passed to a classification head. Model performance was evaluated via accuracy, precision, recall, F1-score, and confidence scores, using cross-validation and test splits to ensure generalization.

5.3 User Interface Integration

Flask's templating engine (Jinja2) dynamically renders classification results and report download links. Secure file upload and user authentication workflows enable personalized interactions and data privacy.

5.4 Execution Requirements

- **Hardware:** NVIDIA CUDA-enabled GPU recommended; CPU supported for smaller tasks.
- **Software:** Python 3.8+, PyTorch, Flask, OpenCV, SQLite3, ReportLab, FPDF.
- **Security:** Password hashing (e.g., bcrypt) secures credentials.
- **Storage:** Server-side organized storage for uploaded MRIs and generated reports.

5.5 Tumor Size Estimation Formulas

Tumor size metrics are computed from segmented tumor contours in pixels and converted to physical units (mm):

$$\text{Area}(mm^2) = \text{Area}_{\text{pixels}} * (\text{pixel\_to\_mm})^2$$

Where

$$\text{Pixel\_to\_mm} = 180\text{mm}/\text{image width(pixels)}$$

$$\text{Diameter(mm)} = 2 * \sqrt{\frac{\text{Area}(mm^2)}{\pi}}$$

$$\text{Perimeter(mm)} = \text{perimeter}_{\text{pixels}} * \text{pixel\_to\_mm} * 0.85$$

The factor 0.85 corrects for pixel discretization effects in contour length estimation.

6. Results and Discussion

6.1 Model Evaluation Results

The proposed hybrid model, combining ResNet50 CNN and Swin Transformer V2-B, was evaluated on a test set of 1,256 MRI images. It achieved an overall accuracy of 98.73%, indicating excellent performance in brain tumor classification.

Class	Precision	Recall	F1-Score	Support
No Tumor	0.99	0.99	0.99	350
Glioma	0.99	0.98	0.99	300
Meningioma	0.96	0.99	0.98	306
Pituitary	1.00	1.00	1.00	300

Table 1: Classification Metrics

The model performed best on pituitary tumors, achieving perfect scores. Minor misclassifications were observed mainly between glioma and meningioma due to their visual similarity.

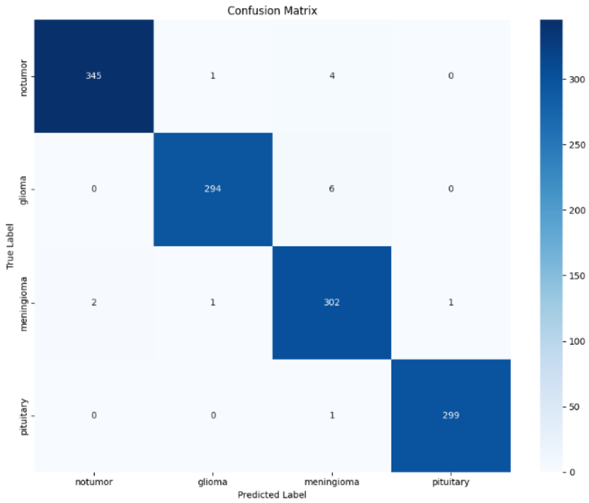

Figure 3: Confusion Matrix

As shown in Figure 3, the confusion matrix shows strong classification capability, with very few misclassified samples. For example, 294/300 glioma images were correctly identified, and all pituitary tumors were classified perfectly.

These results confirm the model's robustness and clinical relevance in detecting and differentiating brain tumor types.

6.2 Training and Validation Analysis

The hybrid model was trained for 20 epochs using an 80:20 train-test split. The training process was monitored using loss and accuracy metrics on both the training and validation sets.

As shown in Figure 4, both training and validation loss decreased steadily, indicating effective learning with minimal signs of overfitting. The validation accuracy stabilized around 98%, confirming the model's strong generalization capability on unseen MRI data.

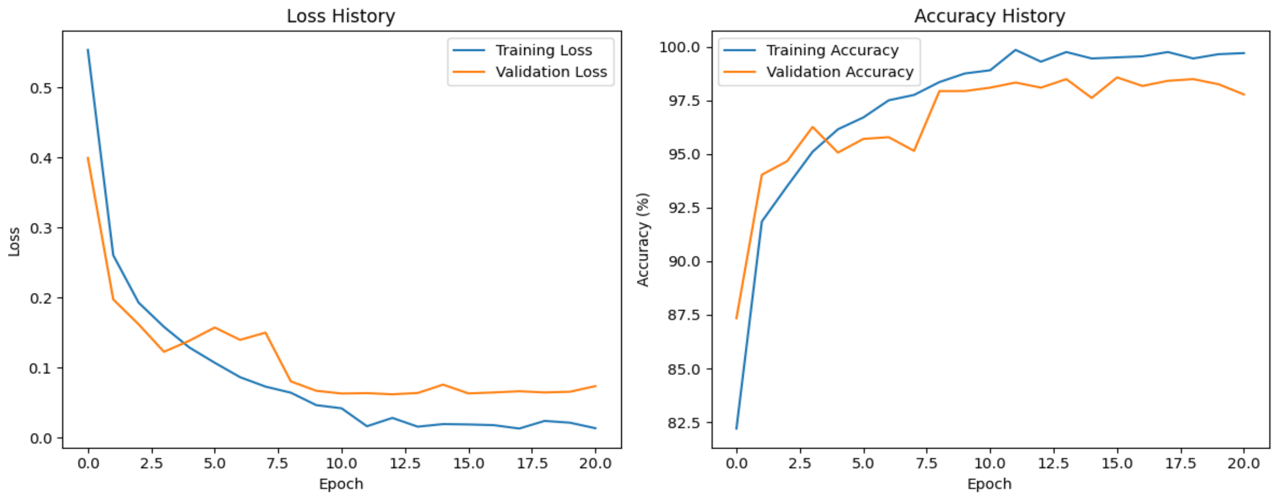

Figure 4: Training and Validation Loss and Accuracy Plots

These results demonstrate that the model converged well during training and maintained high predictive performance throughout.

6.3 Tumor Analysis Report Interface (Final Output)

The system produces a detailed tumor analysis report accessible via a dynamic user interface, as depicted in Figure 5. The report displays the identified tumor type alongside the model's confidence score, providing an interpretable summary of diagnostic results.

Moreover, the report includes quantitative tumor size metrics — namely area (in mm²), perimeter (in mm), and diameter (in mm). These measurements are computed from segmented tumor contours on MRI scans, with pixel-to-millimeter conversion applied to provide clinically meaningful dimensions. The quantitative data supplements the classification by offering additional insight into tumor extent, which can be valuable for treatment planning and monitoring. To enhance clinical usability, the system offers a PDF export feature, allowing users to download and archive the tumor analysis report for offline review or consultation.

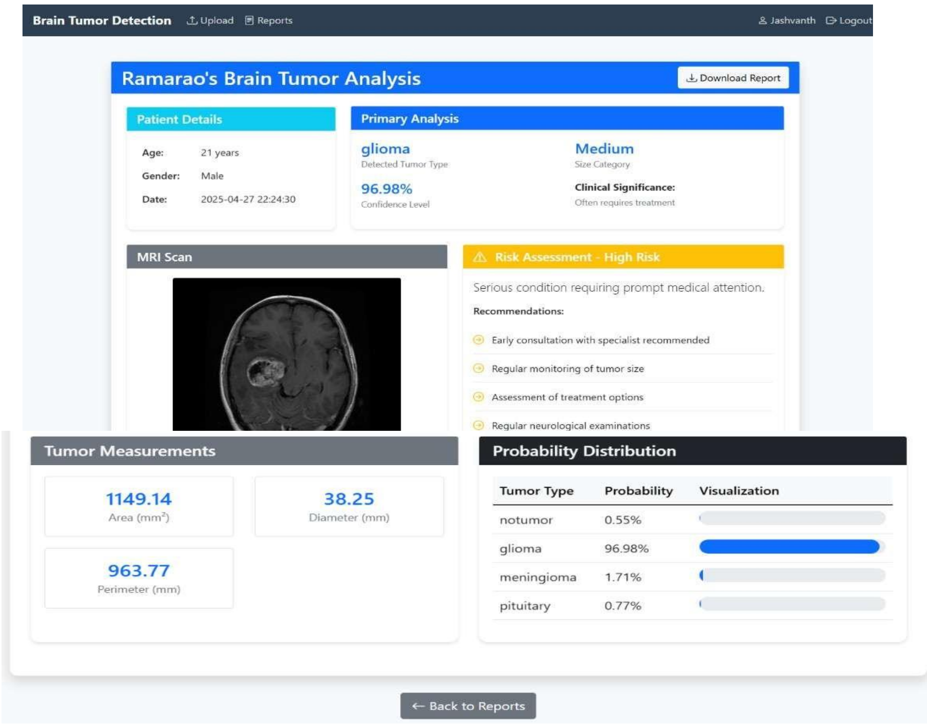

Figure 5: The Tumor Analysis Report Interface

7. Conclusion and Future Scope

7.1 Conclusion

The NeuroShield System employs a hybrid deep learning model combining ResNet50 CNN and Swin Transformer V2-B, achieving a high accuracy of 98.73% in classifying brain tumors from MRI scans. It effectively distinguishes between glioma, meningioma, pituitary tumors, and healthy cases, demonstrating excellent precision and recall. The system also provides detailed tumor size estimation, which adds valuable clinical information for treatment planning. Its strong performance and robustness highlight its potential as a reliable tool to assist healthcare professionals in early diagnosis. Overall, this integrated approach enhances diagnostic accuracy and supports informed clinical decision-making.

7.2 Future Scope

Future enhancements of the NeuroShield System may focus on integrating multiple MRI slices or volumetric data to capture richer spatial and contextual information, thereby improving tumor detection accuracy and detailed size estimation. Real-time multi-slice MRI analysis can further accelerate diagnosis in clinical settings. Expanding the classification scope to include additional tumor types will broaden its diagnostic utility. Integration with hospital information systems (HIS) could streamline clinical workflows, improving usability for medical practitioners. Further improvements in AI performance can be achieved through continuous training with larger and more diverse datasets. Moreover, incorporating longitudinal patient monitoring through sequential MRI analysis would enable tracking tumor progression or treatment response, thereby supporting more dynamic and personalized clinical decision-making.

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