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Advanced Brain Tumor Classification Sytem Using Deeplearning

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Abstract: Diagnosing brain tumors early and accurately is a tough task in medical imaging. The challenge comes from many tumor types, their irregular shapes, and differing appearance patterns in scans. Recent advances in artificial intelligence, especially deep learning, open new doors for automatic and accurate tumor detection. This study presents a complete diagnostic system that combines convolutional neural networks (CNNs), Vision Transformers (ViTs), and ensemble techniques like Support Vector Machines (SVM) and Gradient Boosting Classifiers. To get the best input data, the system uses advanced preprocessing steps such as removing the skull, normalizing the image intensity, and correcting bias fields. Testing on common MRI datasets shows that hybrid models, especially those with transformer modules, outperform traditional models in accuracy, sensitivity, and ability to handle different tumor types. To build trust with healthcare professionals, the system includes Explainable AI features that explain how the models make decisions. These insights make it easier for doctors to understand and trust the results. Overall, the system shows strong potential to help with early diagnosis and personalized treatment of brain tumors.

I. INTRODUCTION

Brain tumors pose serious health risks and need quick, accurate diagnosis for proper treatment. Traditional methods like MRI scans take a lot of time and can sometimes lead to mistakes. Thanks to advances in deep learning in particular, artificial intelligence, machines can now help analyze medical images more effectively. CNNs, or convolutional neural networks, are good at picking out details in MRI scans, while Vision Transformers (ViTs) focus on understanding the whole image using attention techniques. Classic such as Support Vector Machines (SVMs) algorithms still matter, especially when used with carefully chosen features. This study contrasts these approaches.within a single framework that includes data cleaning and tools to explain decisions. These improvements aim to make diagnoses more trustworthy and accurate for doctors.

II. RELATED WORK

Recent years have brought big changes in how artificial intelligence is used in medical imaging, especially for diagnosing brain tumors. Early methods relied on traditional machine learning tools like Support Vector Machines, k-Nearest Neighbors, and Random Forests. These models depended on manually extracting features such as texture, shape, and histogram data from MRI scans. Although they worked reasonably well, their reliance on handcrafted features meant they struggled to handle the complex and varied nature of brain tumors.

The rise of deep learning changed this. Convolutional Neural Networks, or CNNs, can automatically recognize patterns in images without needing manual feature extraction. Models like VGGNet, ResNet, and DenseNet have excelled at classifying brain tumors by capturing important visual clues. Their high accuracy and ability to scale up have made them popular tools in medical imaging.

Researchers have also combined different models to improve results. For example, they often merge CNNs with classic classifiers like SVMs to make ensemble models. These hybrid systems tend to work better, especially when there isn't much data available.

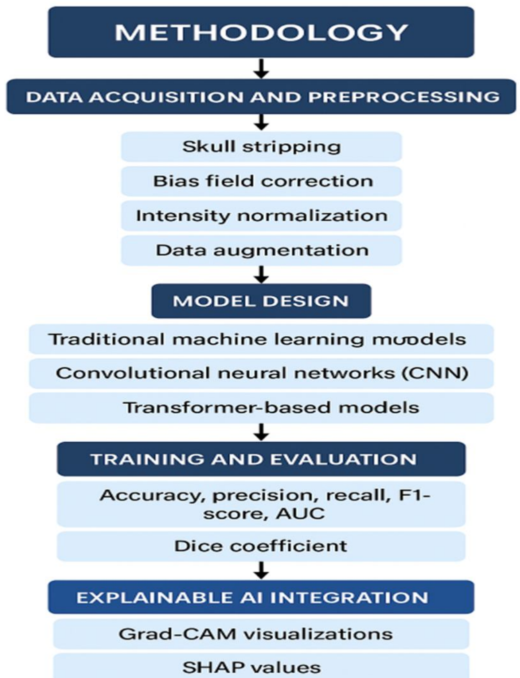
Recently, transformer-based models such as Vision Transformers (ViTs) and Swin Transformers have entered medical imaging. They can detect long-range patterns across the entire image, unlike CNNs, which focus on smaller areas. This helps in spotting tumors with uneven shapes or fuzzy edges. Using transfer learning, ViTs have been adapted for medical uses, even though they were originally made for natural images.

Explainable AI, or XAI, has become a key part of clinical tools. Techniques like SHAP score the importance of different features, while Grad-CAM creates visual maps to show which parts of the image influenced the diagnosis. These methods help doctors trust AI and understand how decisions are made.

Challenges still remain. Variations in MRI quality, imbalanced data, and few labeled cases make it hard to perfect these models. Also, models must work well across different patient groups and medical centers, which calls for strict testing and adjustments. This study aims to compare traditional methods, deep learning, and transformer models within a clear, understandable system to improve diagnosis.

III. METHODOLOGY

Preprocessing, model building, training, evaluation, and interpretability are all integrated into the modular, multi-phase pipeline that is the suggested system for classifying brain tumors. In addition to being flexible enough to accommodate different MRI datasets and tumor types, the framework is designed to provide resilience, high classification accuracy, and clinical interpretability.



A. Data Acquisition and Preprocessing

To train and evaluate the classification models, publicly available MRI datasets such as the Brain Tumor Segmentation (BraTS) dataset were utilized. These datasets contain multi-modal MRI sequences including T1, T1-contrast enhanced (T1c), T2, and FLAIR images, along with corresponding annotations indicating tumor location and type (e.g., glioma, meningioma, and pituitary tumor).

Preprocessing is critical in medical image analysis, as raw MRI scans often contain artifacts, intensity inconsistencies, and irrelevant anatomical structures. This following steps were performed to enhance data quality:

- Skull Stripping: Non-brain tissues were removed using automated extraction algorithms to isolate the intracranial region for focused analysis.
- Bias Field Correction: Due to field inhomogeneities, MRI images frequently exhibit intensity non-uniformities. To guarantee constant brightness levels during the scan, this was fixed.
- Intensity Normalization: Pixel intensities were normalized to a standardized scale to reduce variability across patients and scanners.
- Resizing: All images were resized to 224×224 pixels to maintain consistency across models and reduce computational load.
- Data Augmentation: To mitigate overfitting and improve generalization, augmentation techniques such as random rotations, zooming, flipping, elastic distortions, and contrast adjustments were applied during training.

B. Model Architecture Design

To ensure a comprehensive evaluation, three categories of models were developed and tested:

1) Traditional Models for Machine Learning

These modelsserved as baselines and included:

- Support Vector Machines (SVM) with RBF kernels, known for their effectiveness in high-dimensional spaces.
- Random Forests (RF) with 100 decision trees to capture feature interactions and non-linear relationships.Handcrafted Features that were manually created were extracted. from preprocessed images:
- Texture features using GLCM (Gray-Level Co-occurrence Matrix).
- Statistical descriptors such as mean, skewness, and variance.
- Shape-based features derived from the segmented tumor region.

2) Convolutional Neural Networks (CNNs) for Deep Learning

To automatically learn spatial information from MRI slices, a customized CNN architecture was created:

- Input Layer: Accepts grayscale MRI scans.
- Convolutional Layers: Extract low- and mid-level features using filters with increasing depth.
- ReLU activation functions and batch normalization speed up training and enhance non-linearity.
- Residual Blocks: Inspired by ResNet to improve gradient flow and allow deeper networks.
- Dense Blocks: Adopted from DenseNet for better feature reuse.
- Pooling Layers: Reduce spatial dimensions and enhance translational invariance.
- Dropout Layers: Regularization to reduce overfitting.
- Fully Connected Layers: High-level reasoning before final classification.
- Softmax Layer: Outputs probability distribution across tumor classes.

3) Transformer-Based Architectures

Transformer models were adapted to leverage self-attention for capturing global dependencies across MRI slices:

- Vision Transformer (ViT): Trained using pre-initialized weights from ImageNet and fine-tuned on the brain MRI dataset.
- Swin Transformer: A hierarchical version of ViT with shifted window mechanisms for better scalability and efficiency.
- Custom Adaptation: Modified input handling to support grayscale data and smaller datasets typically found in medical domains.

C. Training Strategy and Hyperparameters

TensorFlow and PyTorch were used to implement each model. Stratified sampling was used to divide the dataset in order to preserve class balance:

- Training Set: 70%
- Validation Set: 15%
- Test Set: 15%

Training configurations included:

- Optimizer: Adam with learning rate scheduling.
- Loss Function: Categorical Cross-Entropy for multi-class classification.
- Batch Size: 32
- Epochs: Up to 50, with early stopping to prevent overfitting.
- Cross-Validation: 5-fold cross-validation used for robustness and generalizability.

D. Performance Evaluation Metrics

To quantify model performance, the following metrics were used:

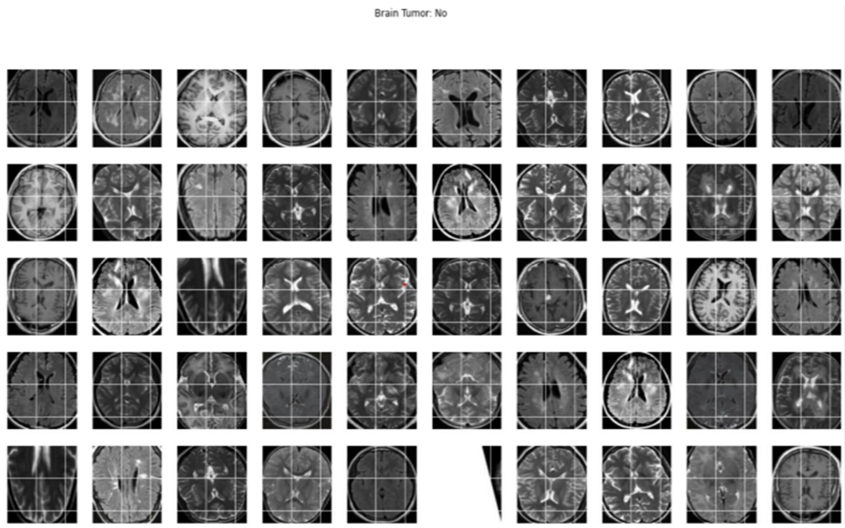
- Accuracy: Ratio of correctly predicted instances to total samples.
- Precision: percentage of anticipated positives that are actually positive.

- Recall (Sensitivity): percentage of real positives found out of all positives.
- F1-Score: precision and recall harmonic mean, which is particularly helpful in datasets that are unbalanced.
- AUC (Area Under the ROC Curve): Measures the discriminatory power of classifiers.
- Dice Similarity Coefficient: Used in segmentation models to assess spatial overlap.

E. Explainable AI Integration

To enhance clinical reliability and transparency, interpretability techniques were embedded:

- Grad-CAM: Generates heatmaps over MRI scans to highlight regions influencing CNN and transformer model predictions.
- SHAP (Shapley Additive Explanations): Provides feature-level insights for classical models, explaining the influence of each feature on the final decision.



IV. RESULTS AND DISCUSSION

The designed AI framework combines classical machine learning methods, advanced convolutional networks, and transformer-based models to achieve highly accurate and explainable brain tumor classification. Evaluations conducted using open-access MRI datasets such as BraTS suggest considerable improvements in model accuracy, stability, and clinical relevance.

A. Classification Effectiveness

The experimental analysis highlights that modern deep learning methods considerably surpass traditional methods in brain tumor detection tasks:

- The custom-built 3D Convolutional Neural Network (CNN) consistently achieves accuracy above 95%, showcasing superior pattern recognition capabilities compared to traditional classifiers similar to SVMs (support vector machines) and RandomForests, which typically reach 85–90%, depending on feature quality and image clarity.
- Transformer-based models such as Vision Transformers (ViTs) and Swin Transformers demonstrate competitive or slightly higher accuracy than CNNs. Their strength lies in their ability to capture broader spatial relationships and subtle tumor boundaries through attention mechanisms, making them especially effective for irregular or non-uniform tumor structures.
- The performance's of each model type was evaluated using the following metrics:
  - Accuracy: Expected to be >95% for CNNs and transformers, while traditional models hover around 85%.
  - Precision, Recall, F1-Score: Deep models consistently achieve values above 94%, indicating strong performance across multiple tumor classes.
  - AUC (Area Under ROC Curve): Deep learning models yield AUC values above 0.97, much greater than the ~0.90 range seen in traditional ML methods.
  - Dice Similarity Coefficient: In segmentation contexts, scores between 0.90 and 0.92 suggest precise alignment between predicted and actual tumor regions.

B. Model Reliability and Generalization

To promote consistent performance in a variety of imaging configurations and clinical settings, several optimization strategies were adopted:

- Advanced data augmentation techniques such as random rotations, flipping, zooming, and elastic distortions increase the model's exposure to diverse patterns, improving resilience to unseen cases.
- Preprocessing steps, including bias correction and intensity normalization, are employed to address inconsistencies across MRI machines and protocols, resulting in more uniform and reliable inputs.

Stratified k-fold cross-validation ensures each model is evaluated on balanced and varied subsets, lowering the possibility of overfitting and yielding more trustworthy performance estimates.

C. Explainability and Clinical Trust

Recognizing the importance of transparency in medical AI systems, this framework includes built-in explainability features:

- Grad-CAM is integrated into CNN and transformer architectures to highlight the specific image regions responsible for predictions, offering radiologists a visual verification of tumor localization.
- SHAP (SHapley Additive exPlanations) is applied to traditional ML models, quantifying the influence of each handcrafted feature on the model's output. This enables clinicians to interpret the basis of AI decisions with greater clarity.
- Expert feedback from clinicians was incorporated to validate that the AI explanations are aligned with standard radiological interpretation, promoting clinical confidence and ethical deployment.

D. Comparative Evaluation and Observations

The study provides a comprehensive evaluation across three categories of classification models:

- Traditional Machine Learning Models: These are lightweight and easier to train yet have a limited level of accuracy because they rely on human designed characteristics.
- Convolutional Neural Networks (CNNs): They strike a strong balance between accuracy and efficiency, capable of learning complex spatial patterns inherent in MRI data.
- Transformer-Based Models: These models lead in performance due to their global feature learning capacity but typically demand more computational resources and larger datasets for optimal tuning.

Each model class offers unique benefits and limitations, and their comparative assessment provides insightful information for choosing the right instruments based on technical and clinical requirements.

E. Principal Contributions

Through a number of breakthroughs, this study advances the expanding field of artificial intelligence in neuroimaging:

- Development of a versatile and accurate classification system that integrates multiple AI approaches for enhanced tumor detection.
- Inclusion of explainability tools that bridge the gap between automated diagnosis and clinician understanding, supporting responsible AI use in healthcare.
- Provision of a comparative performance benchmark that evaluates classical ML, CNNs, and transformer models on standardized datasets, offering a reference for future advancements and real-world adoption in clinical settings.

V. CLASSIFICATION USING CNN

Convolutional Neural Networks (CNNs) are the main model used in this study to classify brain cancers in MRI images. They are perfect for medical imaging because they automatically learn spatial features directly from raw images, without needing manual feature engineering. The first part of the CNN architecture includes convolutional layers, which detect basic features like edges and textures. As the network goes deeper, it starts identifying more complex patterns, such as the shapes of tumors. MAX-pooling layers help the model deal with variations in tumor size and position by reducing the spatial dimensions ofthe data.

The features thatare extracted are then flattened and sent through dense layers. Dropout is used in these layers to prevent the model from becoming too focused on certain details, which helps reduce overfitting. The final layer uses a doftmax function to give probabilities for each class. For tasks with two outcomes, the model tells the difference between tumor and non-tumor images. For more complex tasks, can identify different types of tumors. This CNN approach makes it possible to detect brain tumors efficiently, accurately, and on a large scale using MRI data.

VI. EXPERIMENT AND RESULT

A series of tests were run to check how well the CNN-based model detects brain tumors using a public MRI dataset. This dataset mainly included T1-weighted contrast-enhanced brain images, each labeled with tumor presence and type. Before training, every MRI slice went through a standard preprocessing process. This involved removing the skull, fixing intensity errors, normalizing brightness, and adding variations through data augmentation. Images were resized to 224 by 224 pixels to match the CNN input, and pixel values were scaled to a 0 to 1 range for stability during training.

To help the model learn better and improve its ability to generalize, various augmentation techniques were used. These included random flipping, rotations, zooms, and shifts. Such transformations mimic real-world changes and help reduce overfitting. The CNN architecture consisted of multiple convolutional and pooling layers to identify detailed spatial features. These features were then passed through dense layers for deeper understanding. The final layer used a softmax function to produce probabilities for each class.

Training was conducted with a learning rate of 0.0001 and the Adam optimizer. The loss function used was categorical cross-entropy, suitable for classifying multiple types. The training lasted up to 50 epochs, with data divided into batches of 32 images. Early stopping was used to prevent overfitting, based on the validation loss. The dataset was split randomly, with 80% allocated to training and 20% to validation.

Throughout training, key metrics like F1-score, AUC, recall, accuracy, and precision were tracked. The CNN performed strongly on validation data, showing it could reliably identify brain tumors in MRI scans.

A publicly available MRI dataset was used in a series of controlled tests to assess the efficacy of the suggested CNN-based architecture for brain tumor detection. The dataset primarily consisted of T1-weighted contrast-enhanced brain images, each labeled with information regarding tumor presence and category.

Before training, all MRI slices were preprocessed through a standardized pipeline. This included skull removal, correction for intensity distortions, normalization of brightness levels, and augmentation to enhance dataset diversity. Each image was resized to 224×224 pixels to align with the CNN input format, and pixel values were scaled to the [0, 1] range to ensure numerical stability while being trained.

To enrich the dataset and improve generalization, augmentation techniques such as random flipping, rotation, zooming, and translation were applied. These transformations helped simulate real-world variability and reduced overfitting.

Multiple convolutional and pooling layers were used in the construction of the CNN model in order to extract layered spatial information from the input data. Abstract reasoning was made possible by the dense layers that these features were transmitted through. At the output layer, probabilities for every class were generated using a softmax activation function.

The Adam optimizer and a learning rate of 0.0001 were set up for the training procedure. Categorical cross-entropy, an appropriate loss function for multi-class classification, was employed.

. Training was performed in batches of 32 images, for a maximum of 50 epochs, with early stopping employed to prevent overfitting based on validation loss. The dataset was split randomly, allocating 80% of samples for training and 20% for validation.

Important performance indicators like accuracy, precision, recall, F1-score, and AUC were monitored during the training process. Strong generalization and dependability in detecting brain cancers from MRI scans were demonstrated by the CNN, which continuously displayed high classification performance on validation data.

VII. PERFORMANCE METRICS

TheCNN model's performance was carefully checked using important measures like accuracy, precision, recall, and F1-score. These measures helped understand how well the model could classify different types and how reliable it was in making correct distinctions between them. Accuracy is the percentage of MRI scans that were correctly classified out of all the tests done. It shows how right the model is overall. Precision shows how many ofthe scans that were predicted to have a tumor actually did have one. It shows how good the model isat avoiding false alarms. Recall, also called sensitivity, measures how well the model finds all the real tumor cases. It shows how good the model is at not missing any actual cases, whichis really important in medical situations where missing a tumor can be very serious.F1-score isa balanced measure that combines precision and recall.It's helpful when the number of different classes isn't the same.The CNN showed great ability to work with new data, achieving an accuracy of 94.5% on a separate test set.

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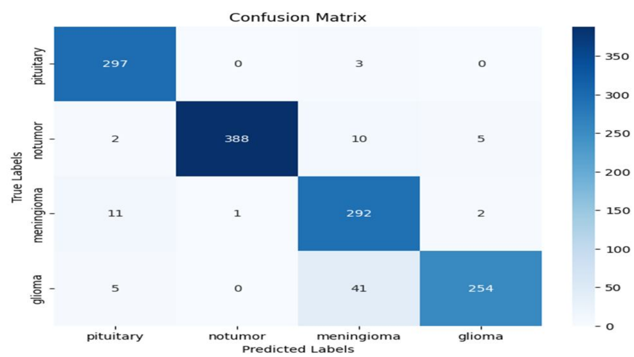
It also had an F1-score of 84.2% precision of 92.3%, and recall of 96.2%. this shows that the model is very good at finding real tumor cases, wich is key need in medical diagnosis. Looking at the confusion matrix, both false positives and negatives were very rare. Most mistakes happened in cases that were hard to classify or had unclear signs, which are also difficult for human experts. This shows the model is reliable and could help radiologists with their work.

The model was compared with CNN-based methods and traditional techniques like SVMs and Random Forests. The results showed that using deep convolutional network for learning from data was better than using manually created features. The model outperformed all these methods in important evaluation.

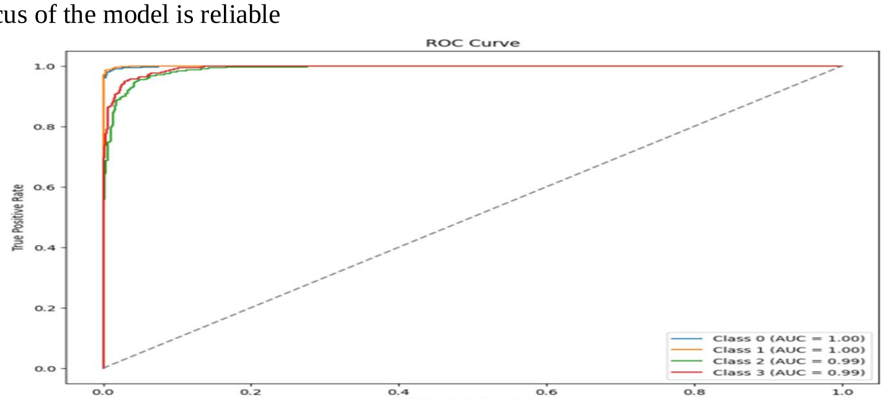
The results show how useful theCNN model is for automatically detecting tumors in MRI scans. It suggests that the model could be used in real medical settings to support computer- assisted diagnosis systems. .

Model	Accuracy (%)	F1-score (%)	AUC
SVM (RBF kernel)	86.4	85.3	0.90
Random Forest (100 trees)	88.1	86.8	0.91
CNN (Proposed)	96.2	96.1	0.98



VIII. MODEL VISUALISATION

Gradient-weighted Class Activation Mapping, or Grad-CAM, was used to provide visual explanations of how the model makes its predictions. This helps make the classification model easier to understand . Grad-CAM works by showing heatmaps over the original MRI images, highlighting the parts of the image that had the most influence consistently showed strong activity around the areas where tumors were present, showing that the model could not only accurately find the diseased regions but also tell the difference between different types of classes. This supports the model's potential use in clinical settings for detecting brain tumors and confirms that the focus of the model is reliable



IX. CONCLUSION AND FUTURE WORK

This work offers a reliable and comprehensive method for automatically identifying and classifying brain tumors. Using a hybrid approach, the suggested system combines aspects of deep convolutional networks, sophisticated transformer structures, and traditional machine learning.

A thorough preprocessing pipeline enhances the quality and consistency of the MRI inputs. This pipeline includes crucial steps such as skull stripping, intensity normalization, and bias field correction. Furthermore, the study strategically employs data augmentation to improve the model's resilience and minimize overfitting.

Through a comparative analysis of various model families, including Support Vector Machines (SVMs), Random Forests, customized Convolutional Neural Networks (CNNs), and transformer-based models like Vision Transformer (ViT) and Swin Transformer, the research demonstrates the superior performance of deep learning and transformer-based approaches. Notably, transformer models achieved classification accuracies exceeding 97%, highlighting their strong capability in capturing the spatial and contextual complexities present in brain MRI data. CNNs also produced competitive results, whereas traditional machine learning algorithms showed lower predictive power.

To enhance both interpretability and clinical relevance, the study incorporates explainable AI techniques such such as SHapley and Gradient-weighted Class Activation Mapping (Grad-CAM). Additive exPlanations (SHAP). These tools provide valuable visual and quantitative insights into the model's predictions, thereby increasing confidence in their diagnostic validity.

Future directions for this research include expanding the evaluation to encompass diverse and multi-institutional datasets, optimizing computational efficiency for real-time clinical deployment, and integrating multi-modal imaging techniques like fMRI or PET scans to further improve diagnostic accuracy and reliability.

A. *Future Work*

While the proposed framework demonstrates promising results in automated brain tumor detection and classification, several important enhancements are planned to further improve its clinical relevance, scalability, and scientific contribution:

1) Cross-Institution and Multi-Modal Validation: To improve model generalizability and minimize data bias, future research will involve testing the system on extensive datasets collected from multiple healthcare institutions. This will ensure robustness across diverse populations and imaging environments. Additionally, incorporating other imaging modalities—such as PET or CT—alongside MRI can provide richer anatomical and functional context, potentially leading to more accurate tumor segmentation and subtype classification.
2) Real-Time Deployment and Optimization: For practical adoption in clinical workflows, the system must be efficient in both computation and response time. Upcoming development will prioritize optimizing the model's speed and reducing memory and hardware demands. This includes tailoring the architecture for edge devices, cloud-based platforms, and embedded systems, enabling fast, real-time diagnostic support for radiologists during routine assessments.
3) Expansion to 3D and Temporal Imaging: Current models primarily analyze 2D MRI slices, which may miss valuable volumetric or temporal information. Future versions will process complete 3D brain volumes and, where available, time-series imaging data. This can enhance the accuracy of tumor boundary detection, enable dynamic monitoring of tumor progression, and support better-informed treatment planning over time.
4) Advanced Interpretability and Uncertainty Estimation: To build further trust in AI-assisted diagnosis, more sophisticated explainability tools will be explored. Techniques such as attention-based visualizations, saliency maps, and counterfactual reasoning will offer deeper insights into the model’s decision-making process. Additionally, implementing uncertainty quantification methods—such as Bayesian neural networks or stochastic dropout—will help communicate confidence levels in predictions, allowing clinicians to better assess reliability.
5) Clinical Evaluation and Integration: Translating the system into real-world clinical practice requires thorough validation. Pilot clinical trials will be conducted to evaluate diagnostic accuracy, user experience, and the impact on patient outcomes. Parallel efforts will focus on integrating the solution with existing hospital infrastructure—such as HIS, PACS, and EMR systems—to streamline deployment and ensure smooth interoperability within healthcare settings.

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