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ENHANCING THE ROLE OF ARTIFICIAL INTELLIGENCE IN DIFFERENTIAL DIAGNOSIS OF MALIGNANT AND BENIGN BRAIN TUMORS USING MRI IMAGES

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Abstract

Overlapping MRI features of malignant and benign brain tumors increase uncertainty in radiological interpretation, may lead to additional examinations, and can delay treatment decisions. The aim of this article is to substantiate a clinical and methodological algorithm for enhancing the diagnostic value of artificial intelligence in multiparametric MRI analysis. The proposed approach integrates T1, T2, FLAIR, DWI/ADC, SWI, perfusion imaging and post-contrast 3D T1 sequences with tumor segmentation, radiomic features, deep neural networks and explainable AI tools. The model includes image standardization, automated delineation of the tumor and peritumoral changes, classification of malignancy probability, and interpretable heat-map support for radiology reporting. Validation metrics, a clinical decision matrix and implementation criteria are proposed in accordance with STARD, CLAIM, TRIPOD+AI and AI-RANO principles. In conclusion, AI may strengthen radiological decision-making by quantifying subtle morphological, textural and volumetric signs relevant to differentiating malignant from benign brain tumors on MRI.

Keywords: artificial intelligence, brain tumor, deep learning, differential diagnosis, MRI, radiomics, segmentation

INTRODUCTION

Brain tumors exhibit substantial clinical, morphological, and molecular heterogeneity, and a single imaging feature is often insufficient to determine whether a tumor is malignant or benign. The 2021 World Health Organization classification of central nervous system tumors placed greater emphasis on molecular markers alongside histological features [1]. Accordingly, an MRI report should not merely establish the presence or absence of a tumor, but should also assess its probable biological behavior, degree of invasiveness, and the subsequent need for biopsy or surgery.

MRI is the principal imaging modality for detecting brain tumors. T1-weighted, T2-weighted, fluid-attenuated inversion recovery (FLAIR), diffusion-weighted imaging/apparent diffusion coefficient (DWI/ADC), susceptibility-weighted imaging (SWI), perfusion, and post-contrast 3D T1-weighted sequences provide information on tumor margins, necrosis, hemorrhage, edema, infiltration, and patterns of contrast

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enhancement [2]. However, some benign tumors may show avid enhancement or peritumoral edema, whereas malignant tumors may initially show only minimal enhancement. Consequently, radiological differentiation may be challenging between meningioma and metastasis, low-grade glioma and nonspecific gliosis, hemangioblastoma and a metastatic lesion, and lymphoma and high-grade glioma.

AI-based image analysis may help reduce this diagnostic complexity. Through segmentation, classification, radiomic feature extraction, and probabilistic risk scoring, deep learning models quantify differences in texture, shape, and signal intensity that may be difficult for a radiologist to distinguish visually [3-6]. AI should therefore be regarded not as an autonomous diagnostic tool, but as a decision-support system that provides an evidence-supported second opinion to the radiologist and the clinical team.

The object of this study is the diagnostic imaging framework for MRI-based assessment of brain tumors. Its specific focus is the clinical, methodological, and validation criteria for AI-assisted differentiation between malignant and benign tumors.

The aim of the study is to develop an original algorithm that enhances the role of AI in differential diagnosis using multiparametric MRI and to substantiate it with evaluation criteria relevant to clinical practice. The objectives are to: (1) standardize the MRI protocol; (2) systematize AI-readable imaging features of malignant and benign tumors; (3) describe the segmentation and classification pipeline; (4) define metrics for diagnostic accuracy, calibration, and explainability; and (5) develop recommendations for the safe incorporation of AI outputs into radiology reports.

MATERIALS AND METHODS

This article presents a scientific and methodological model intended to inform a subsequent clinical validation study. The model draws on STARD for diagnostic accuracy studies, CLAIM for reporting AI developments in medical imaging, TRIPOD+AI for clinical prediction models, and AI-RANO principles for AI validation in neuro-oncology [7-10]. When this approach is applied to real-world clinical data, the data must be anonymized, ethics committee approval must be obtained, and data leakage must be prevented at the patient level.

The proposed clinical database is to include T1, T2, FLAIR, DWI/ADC, SWI, post-contrast 3D T1, and, where available, perfusion sequences acquired on 1.5 T or 3 T MRI scanners. The reference standard is to comprise histopathological findings from surgical specimens or stereotactic biopsy, or at least 12 months of longitudinal follow-up for clearly benign tumors. All images are to be converted from DICOM into a standardized volumetric format and processed to standardize voxel size, signal intensity, and spatial alignment.

The inclusion criteria comprise MRI-based suspicion of a brain tumor, availability of a contrast-enhanced examination, a complete set of core sequences, and an available reference standard. The exclusion criteria comprise severe motion artifacts, an incomplete MRI protocol, confounding changes in the early postoperative period, insufficient clinical information, and inability to anonymize the images.

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Table 1. Inclusion and exclusion criteria for AI-MRI validation

Criterion type	Inclusion criteria	Exclusion criteria	Comment
Clinical	Clinical or MRI suspicion of a brain tumor	No reference diagnosis	Confirmation by biopsy or follow-up is required
Imaging	Available T1, T2, FLAIR, DWI/ADC, and post-contrast 3D T1 sequences	Motion artifacts or missing slices	A uniform protocol improves model robustness
Technical	Complete DICOM metadata and known scanner parameters	Markedly different voxel sizes or corrupted files	Resampling and normalization are required
Ethical	Anonymization and authorization documents are available	Inability to remove personally identifiable information	Data security is mandatory

Source: Compiled by the author.

The AI pipeline comprises four main modules: (1) preprocessing; (2) segmentation of the tumor, edema, and necrotic components; (3) integration of radiomic and deep-learning features; and (4) a classifier that estimates the probability of malignancy. An encoder-decoder architecture such as 3D U-Net or nnU-Net may be used for segmentation, whereas a ResNet-, EfficientNet-, or vision transformer-based model may be used for classification [6,11]. At the output stage, an explainability layer using Grad-CAM, saliency maps, or SHAP shows the radiologist which regions influenced the model decision.

Data are to be partitioned at the patient level: different sequences or repeat examinations from the same patient must not appear in both the training and test sets. Internal validation is to use k-fold cross-validation, whereas external validation is to use data from a different scanner or center. The model's clinical utility is to be assessed not only in terms of high accuracy, but also in terms of calibration, the false-negative rate, inter-radiologist agreement, and its effect on time to decision-making.

Diagnostic performance metrics are calculated using the following expressions:

(1) $\text{Sensitivity} = TP / (TP + FN) \times 100\%$; $\text{Specificity} = TN / (TN + FP) \times 100\%$

(2) $PPV = TP / (TP + FP) \times 100\%$; $NPV = TN / (TN + FN) \times 100\%$

(3) $\text{Dice} = 2 \times |A \cap B| / (|A| + |B|)$,
where A is the expert segmentation and B is the AI segmentation.

(4) $\Delta AUC = AUC(\text{AI-MRI}) - AUC(\text{conventional MRI})$;
$ECE = \Sigma\ |\text{bin accuracy} - \text{bin confidence}|$

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RESULTS

The proposed AI-MRI model consolidates the features used to differentiate malignant and benign tumors within a unified diagnostic pipeline. In conventional MRI interpretation, radiologists assess enhancement, edema, necrosis, and mass effect primarily in qualitative terms; AI quantifies these features using volume, texture, gradients, signal variance, ADC values, and perfusion metrics. The model may therefore be particularly useful for tumors with ill-defined margins, heterogeneous signal characteristics, or limited clinical manifestations.

Table 2 presents the most important MRI features for AI-assisted differential assessment of brain tumors and their algorithmic interpretation.

Table 2. AI-derived MRI features and their clinical significance

MRI feature	AI-extracted feature	Findings favoring malignancy	Findings favoring a benign tumor
Margins and growth pattern	Contour irregularity and infiltration index	Ill-defined, infiltrative margins and spread along white matter tracts	Well-defined capsule, expansile growth, and extra-axial location
Contrast enhancement	Ring configuration, heterogeneity, and enhancement gradient	Ring enhancement with necrosis or avid heterogeneous enhancement	Homogeneous enhancement or a stable dural tail sign
DWI/ADC	ADC histogram and proportion of low-ADC regions	Restricted diffusion and a low-ADC component	Relatively high or uniform ADC values
FLAIR/T2 edema	Ratio of peritumoral edema volume to tumor volume	Extensive infiltrative edema relative to tumor size	Limited reactive edema and well-defined mass margins
Perfusion MRI	rCBV, rCBF, and permeability metrics	Neovascularization and increased rCBV	Low or moderate perfusion activity
SWI/blood products	Microhemorrhages and hemorrhagic signal indices	Association with necrosis and hemorrhagic components	Stable calcification or low-risk blood products

Source: Compiled by the author.

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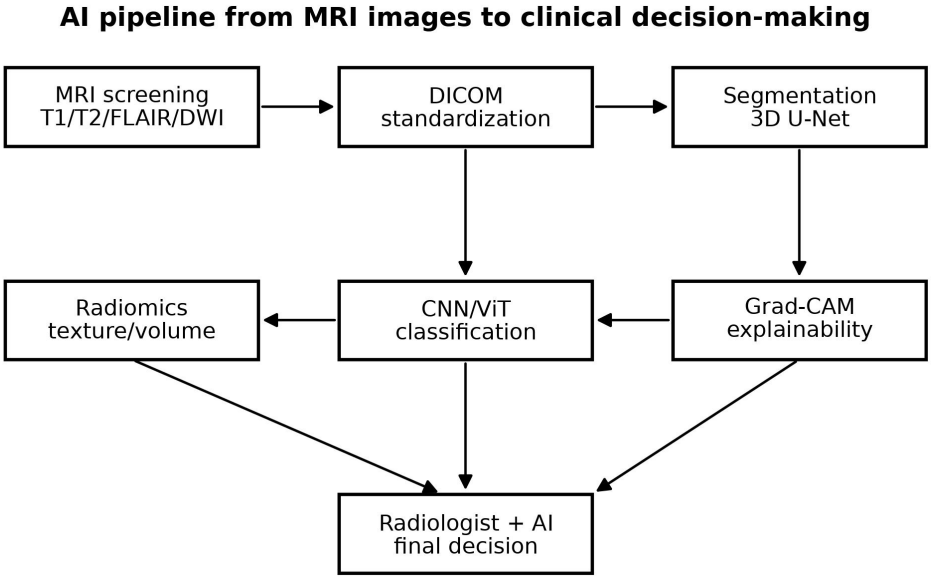


Figure 1. AI-assisted differential diagnostic pipeline based on MRI images

To improve the quality of radiology reports, the AI pipeline should present model outputs not as an isolated malignancy probability, but as a set of verifiable evidence. The segmentation mask, tumor volume, proportion of peritumoral edema, estimated risk category, confidence interval, and explanatory map should be displayed together. This approach reduces the black-box effect and enables the clinical team to discuss the findings.

Table 3. Recommended metrics for evaluating the AI-MRI model

Metric	Definition / calculation	Clinical interpretation	Minimum requirement
AUC	Area under the ROC curve	Overall ability to discriminate between malignant and benign tumors	Stable performance on external testing
Sensitivity	Proportion of malignant tumors correctly identified	Reduces false-negative findings	Prioritized in high-risk groups
Specificity	Proportion of benign tumors correctly classified	Reduces unnecessary biopsies and treatment	Balanced against sensitivity
Dice coefficient	Agreement between AI and expert segmentations	Indicates the reliability of volumetric assessment	Evaluated separately for each tumor component

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Metric	Definition / calculation	Clinical interpretation	Minimum requirement
Calibration	Agreement between predicted probabilities and observed frequencies	Makes AI confidence clinically interpretable	ECE and a calibration curve
Explainability	Regions influencing the decision	Enables radiologist oversight and audit	Heatmap concordance with clinical findings

Source: Compiled by the author.

The clinical decision matrix assigns AI outputs to three risk categories. A low-risk classification may support surveillance for well-circumscribed, homogeneously enhancing, and stable tumors. An intermediate-risk classification calls for additional perfusion MRI, MR spectroscopy, or multidisciplinary team (MDT) review. A high-risk classification warrants prompt decision-making involving a neurosurgeon, an oncologist, and a pathologist, with consideration of biopsy or surgical planning.

Table 4. Clinical decision matrix for incorporating AI outputs into radiology reports

Risk category	AI-MRI feature profile	Suggested wording in the radiology report	Recommended next step
Low	Well-defined margins, low edema index, limited enhancement, and stable structure	A benign tumor is highly likely; longitudinal surveillance is appropriate	Scheduled follow-up MRI and monitoring guided by clinical symptoms
Intermediate	Heterogeneous signal and mixed features of edema and enhancement	Biological behavior is indeterminate; further assessment is required	Perfusion MRI, spectroscopy, or MDT discussion
High	Infiltrative margins, necrosis, low ADC, high perfusion, and extensive edema	Malignancy is highly likely; AI findings are concordant with clinical and radiological data	Neurosurgical consultation and planning for biopsy or surgery
Discordant	The AI heatmap does not correspond to the clinical lesion	The AI output should be interpreted with caution	Expert reassessment and an audit of protocol quality

Source: Compiled by the author.

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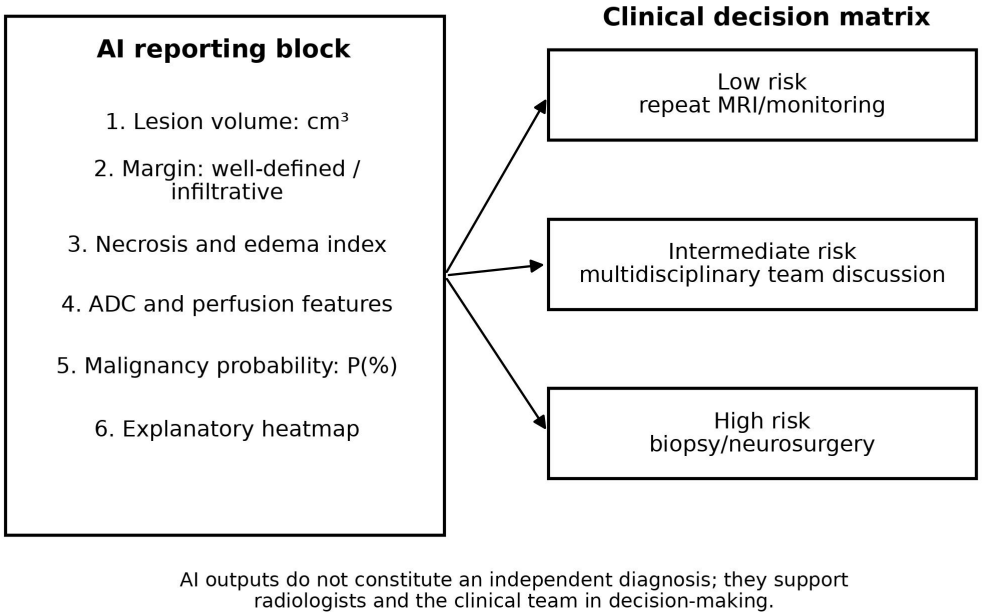


Figure 2. AI reporting block and radiological decision matrix

DISCUSSION

The intensity of contrast enhancement alone is insufficient to determine malignancy in brain tumors. Although contrast enhancement is associated with blood-brain barrier disruption, vascular permeability, and neovascularization, some benign tumors may also enhance avidly. Conversely, certain low-grade gliomas may grow slowly and show minimal enhancement while retaining an infiltrative growth pattern. The central principle for AI is therefore to integrate a combination of features from multiple sequences rather than rely on a single feature.

Standardized Brain Tumor Imaging Protocol (BTIP) approaches improve the comparability of images in clinical trials and provide an important foundation for AI validation [2,12]. The BraTS and The Cancer Genome Atlas (TCGA) glioma collections have established an international benchmarking environment for multimodal MRI segmentation, expert annotations, and radiomics [4,5]. The model proposed in this article adapts this experience to the differential diagnosis of malignant and benign tumors: tumor and edema regions are first delineated, after which radiomic and deep-learning features are combined to generate a risk category that is interpretable to radiologists.

The AI-RANO recommendations call for standardization, external validation, and adherence to good clinical practice criteria before algorithms are introduced into clinical neuro-oncology [9,10]. These requirements are particularly relevant to brain tumors because available datasets are limited, tumor types are unequally represented, and differences in scanners and protocols introduce domain shift. Accordingly, strong

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performance at a single center is insufficient when developing a local model; separate audits across different scanners, age groups, and histological types are required.

Explainable AI enables radiologists to scrutinize model decisions. Confidence in the model output increases when the heatmap corresponds to the tumor center, enhancing rim, or infiltrative FLAIR regions. If the model instead relies on bone, artifacts, skin, or vascular signal, its output should be rejected. This safeguard improves clinical safety and reduces the risks associated with using AI systems without human oversight.

The practical advantages of this approach include reducing variability between radiologists, triaging indeterminate cases, objectively monitoring tumor volume, and providing standardized information for MDT review. Its limitations include the inability to establish a definitive diagnosis without histological confirmation, the potentially malignant-appearing imaging features of some benign tumors, biological differences between pediatric and adult tumors, and insufficient data on rare tumor types.

A three-stage pathway is appropriate for implementation in local practice. In the first stage, a retrospective DICOM archive database is established. In the second, the model is tested independently of radiologists' decisions. In the third, a prospective radiologist-plus-AI workflow is evaluated. At each stage, personal data protection, model version, scanner parameters, and error audits should be documented separately.

CONCLUSIONS AND RECOMMENDATIONS

The role of AI in the MRI-based differential diagnosis of malignant and benign brain tumors is enhanced through the quantitative, reproducible, and explainable assessment of imaging features. By integrating tumor margins, necrosis, edema, ADC, perfusion, and texture, AI supplements radiology reports with more consistent evidence to support clinical decision-making.

The proposed AI-MRI algorithm consists of four practical components: a standardized MRI protocol, automated segmentation, risk classification based on multimodal features, and an explainable report. This pipeline positions AI not as a replacement for radiologists, but as a tool for improving diagnostic accuracy, triaging indeterminate cases, and expediting clinical discussion.

The practical recommendations are to: (1) standardize the MRI protocol to include T1, T2, FLAIR, DWI/ADC, SWI, and post-contrast 3D T1 sequences; (2) establish a local database with diagnoses confirmed by histology or long-term clinical follow-up; (3) evaluate the model using internal and external test sets partitioned at the patient level; (4) present AI outputs together with heatmaps and calibration metrics; and (5) conduct a radiological audit of every false-negative and false-positive case.

Future research should address multicenter validation, separate modeling of pediatric and adult tumors, investigation of radiogenomic associations with molecular markers, and prospective evaluation of the effects of AI outputs on actual clinical decisions and time to treatment.

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