



Multi-Level Brain Tumor Classification From MRI: A Review of Deep Learning Methods, Datasets, Evaluation, and Clinical Challenges

Megha Chalwadi¹, Anam Bangi², Soujanya Rodge³, Sakshi Surwase⁴, Aishwarya Hosale⁵

Student, CSE Department, A. G. Patil Institute of Technology, Solapur, India¹

Student, CSE Department, A. G. Patil Institute of Technology, Solapur, India²

Student, CSE Department, A. G. Patil Institute of Technology, Solapur, India³

Student, CSE Department, A. G. Patil Institute of Technology, Solapur, India⁴

Guide, CSE Department, A. G. Patil Institute of Technology, Solapur, India⁵

Dr. Babasaheb Ambedkar Technological University (DBATU)¹⁻⁵

Abstract: Brain tumor classification from Magnetic Resonance Imaging (MRI) images has become an important area of research with the development of machine learning and deep learning techniques. This review examines the development of MRI-based brain tumor classification from early computer-aided and machine-learning approaches to recent deep-learning methods, with emphasis on Convolutional Neural Networks (CNNs), transfer learning, EfficientNet architectures, Vision Transformers, and hybrid CNN–Transformer models. The review analyzes representative studies, datasets, tumor-classification settings, evaluation measures, and reported findings across the 2000–2026 research period. Common classification categories include glioma, meningioma, pituitary tumors, benign/malignant classes, and no-tumor cases, while some studies also investigate tumor grades. The literature shows a methodological progression from handcrafted texture, shape, and intensity features with conventional classifiers toward end-to-end deep learning and transformer-based systems. However, differences in dataset size, class distribution, preprocessing, and validation strategies make direct comparison of reported performance difficult. Important challenges include limited dataset diversity, class imbalance, external validation, explainability, reproducibility, and clinical generalization. Future directions include larger multi-center datasets, independent validation, explainable artificial intelligence, lightweight models, privacy-preserving learning, multimodal analysis, and human-AI collaboration.

Keywords: Brain Tumor Classification; MRI; Deep Learning; CNN; Transfer Learning; Vision Transformer

I. INTRODUCTION

Brain tumors are serious medical conditions that require accurate and timely diagnosis.

Magnetic Resonance Imaging (MRI) provides detailed information about brain structures and abnormal regions and is therefore widely investigated as an input for computer-aided brain tumor analysis.

Automated classification has received substantial research attention because MRI interpretation can involve differences in tumor size, location, appearance, and image acquisition conditions.

In the development of automated MRI analysis, early research focused on image processing, segmentation, handcrafted texture/shape/intensity features, and conventional machine-learning classifiers.

Later work introduced neural networks and deep learning, followed by transfer learning and more recent architectures such as EfficientNet, Vision Transformers (ViTs), and hybrid CNN–Transformer models.

This progression motivates a review that considers the broader development of the field rather than only recent deep-learning studies.

Brain tumor classification studies commonly consider glioma, meningioma, and pituitary tumors, and some datasets add a no-tumor class.

Depending on the study, the task may distinguish tumor from no tumor, identify tumor type, or classify tumor grade.

The objective of this review is to summarize this methodological progression, compare representative studies, examine datasets and evaluation practices, and identify the research gaps that remain important for reliable clinical use.



II. REVIEW METHODOLOGY

This review was conducted to examine research on brain tumor classification from MRI using machine-learning and deep-learning techniques.

The literature considered the broader development of automated MRI analysis from the early 2000s through 2026, with particular emphasis on classification, feature extraction, conventional machine learning, CNNs, transfer learning, EfficientNet, Vision Transformers, and hybrid CNN–Transformer architectures.

Relevant studies and review papers were identified through scientific databases and publisher platforms including PubMed, ScienceDirect, Springer Nature, Frontiers, MDPI, and related academic sources.

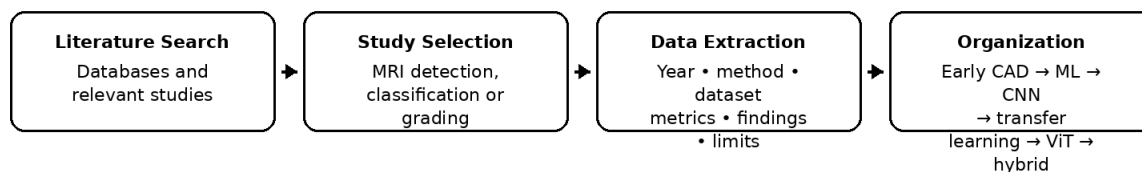
Search terms included combinations of “brain tumor classification,” “MRI brain tumor,” “deep learning,” “CNN,” “transfer learning,” “Vision Transformer,” “EfficientNet,” “machine learning,” and “multi-class brain tumor classification.” Studies were considered relevant when they focused on MRI-based brain tumor detection, classification, or grading and reported identifiable methods, datasets, or evaluation results.

Papers with insufficient methodological information or limited relevance to MRI-based brain tumor analysis were not prioritized.

For each selected study, information was recorded about publication year, method, dataset or setting, classification task, reported evaluation Page 2 measures, key findings, and limitations.

The selected literature was organized by methodological development: early computer-aided/image-processing approaches, conventional machine learning, neural networks and CNNs, transfer learning, efficient architectures, Vision Transformers, and hybrid CNN–Transformer systems.

Review Methodology Flowchart



III. BACKGROUND / THEORETICAL FRAMEWORK

3.1 Magnetic Resonance Imaging (MRI) MRI is a non-invasive imaging technique that provides detailed images of brain anatomy and abnormalities.

MRI scans are widely used as the input modality in automated brain tumor classification research. **3.2 Brain Tumor Classification** Brain tumor classification assigns an MRI image to one of several predefined categories.

Depending on the study, the task may distinguish tumor from no tumor, identify tumor type, or classify tumor grade. Common categories in public multi-class datasets include glioma, meningioma, pituitary, and no tumor. **3.3 Deep Learning for MRI Classification** Deep learning uses multilayer neural networks to learn patterns from data.

In medical-image classification, deep models can learn image features directly from MRI images. Transfer learning is especially useful when the target medical dataset is smaller than the datasets normally used to train large image models. **3.4 Convolutional Neural Networks (CNNs)** CNNs use convolutional operations to learn visual features at different levels.

Earlier layers can learn lower-level structures while deeper layers learn more complex patterns. CNN-based approaches remain an important baseline for brain tumor MRI analysis. **3.5 Transfer Learning** Transfer learning adapts a pretrained model to a new task.

Studies have used pretrained architectures such as VGG, Inception, MobileNet, DenseNet, GoogLeNet, and EfficientNet for MRI classification. **3.6 EfficientNet** EfficientNet is a family of CNN architectures designed to balance performance and computational efficiency.



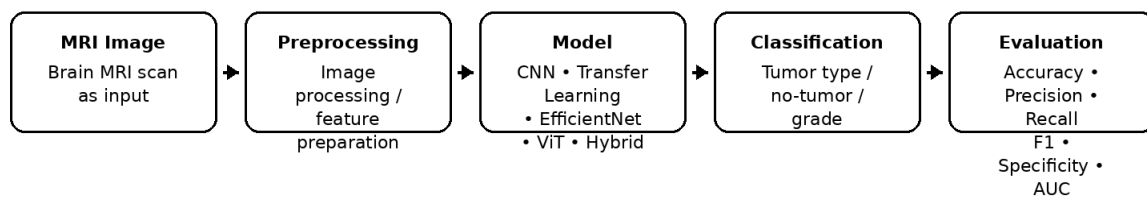
Fine-tuned EfficientNet variants have been investigated for multi-class brain tumor classification, with Grad-CAM used in some work to visualize model attention. 3.7 Vision Transformers Vision Transformers apply self-attention to image patches represented as a sequence.

Recent studies have evaluated fine-tuned Vision Transformer variants and compared them with established CNN architectures. 3.8 Hybrid and Ensemble Approaches Recent research combines CNN and transformer components or uses ensembles of several pretrained models.

Hybrid approaches aim to combine detailed local feature extraction with broader relationships between image regions. 3.9 Evaluation Measures Common measures include accuracy, precision, recall (sensitivity), F1-score, specificity, and area under the ROC curve.

Using multiple measures provides a more complete view of classification behavior, especially when class distributions are not balanced.

MRI Brain Tumor Classification Flowchart



IV. LITERATURE REVIEW

The reviewed research shows a progression from handcrafted image features and conventional classifiers toward neural networks, transfer learning, efficient CNNs, Vision Transformers, and hybrid architectures.

Early work established computer-aided analysis pipelines in which MRI images were processed through region-of-interest definition, feature extraction, feature selection, and classification.

Zacharaki et al. (2009), for example, combined conventional and perfusion MRI with texture, shape, and intensity features and used SVM-based feature selection for tumor type and grade classification.

During the 2010s, conventional machine-learning studies commonly used GLCM, wavelet, texture, shape, and intensity features with classifiers such as ANN, KNN, and SVM.

El-Dahshan et al. (2014) proposed a hybrid pipeline combining segmentation, wavelet-based feature extraction, PCA, and a back-propagation neural network.

Sharma and Marikkannu (2015) investigated a 3D MRI classification framework using region-growing and SVM components.

The deep-learning transition became more visible in the later 2010s.

Fabbri et al. (2017) investigated fully connected and convolutional neural networks for classifying meningioma, glioma, and pituitary tumors.

Deepak and Ameer (2019) used a pretrained GoogLeNet for three-class classification and reported 98% mean accuracy under patient-level five-fold cross-validation.

More recent work has focused on transfer learning and specialized architectures.

Tandel et al. (2020) evaluated an AlexNet transfer-learning CNN across multiple multiclass settings.

Islam et al. (2023) compared VGG19, Page 3 InceptionV3, MobileNet, and DenseNet121 for four-class classification.

Zulfiqar et al. (2023) evaluated EfficientNetB0–B4 and used Grad-CAM for visual explanation.

In 2024, Reddy et al. evaluated fine-tuned Vision Transformer variants on 7,023 MRI images across four classes, while Goceri investigated a combined CNN–Transformer architecture for tumor classification and glioma grading.

More recent 2026 studies continue to compare optimized CNNs, pretrained models, and ensembles, showing that model efficiency, robustness, and generalization remain active research areas.



V. COMPARATIVE ANALYSIS

The comparison indicates a gradual methodological progression from handcrafted feature-based methods and conventional machine learning toward deep CNNs, transfer learning, EfficientNet, Vision Transformers, and hybrid systems.

Reported accuracy values should not be treated as directly comparable because studies use different datasets, class definitions, preprocessing procedures, train/test splits, and validation protocols.

Table 1 summarizes representative milestones across the 2000–2026 period.

The table is intended to show methodological development and is not a ranking of studies.

VI. RESEARCH GAPS AND CHALLENGES

6.1 Limited and Heterogeneous Datasets Many studies rely on public or relatively small datasets.

Differences in MRI scanners, acquisition protocols, image quality, and patient populations can create dataset shift and reduce generalization. **6.2 Generalization and External Validation** A model can perform strongly on its development dataset yet behave differently on external data.

Cross-dataset and multi-center validation are therefore important for assessing robustness beyond a single public dataset.

6.3 Class Imbalance and Dataset Bias Unequal representation of tumor categories can influence learning and evaluation. Dataset construction should be considered when interpreting high performance, particularly for multi-class problems. **6.4 Explainability** Deep-learning models can be difficult to interpret.

Techniques such as Grad-CAM provide visual indications of image regions influencing predictions, but visualization alone does not establish clinical validity. **6.5 Reproducibility** Differences in preprocessing, splitting, augmentation, and evaluation practices make direct comparison and reproduction difficult.

Standardized reporting would improve the usefulness of published results. **6.6 Clinical Translation** High performance on a public dataset does not by itself establish clinical effectiveness.

Independent validation on representative clinical data and evaluation of real workflows are necessary before routine use.

VII. FUTURE SCOPE

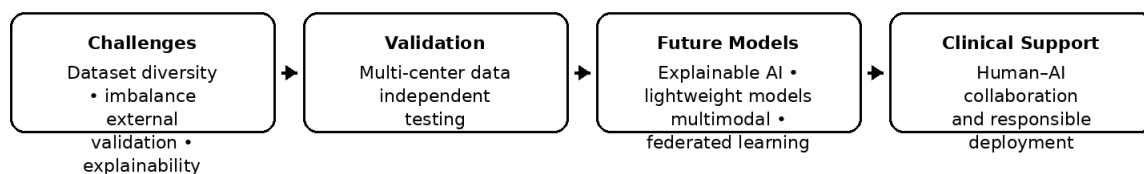
Future research can focus on larger and more diverse multi-center datasets, external validation, explainable AI, multimodal MRI analysis, lightweight architectures, privacy-preserving collaborative learning, and human–AI decision support.

Federated learning may allow institutions to collaborate without directly centralizing patient data, while lightweight models may improve feasibility in resource-constrained settings.

More systematic evaluation of uncertainty and model failure cases would also improve responsible deployment.

Future studies should also report patient-level splits, external test performance, class-wise metrics, and reproducible preprocessing pipelines wherever possible.

Research Gaps to Future Scope



VIII. CONCLUSION

Brain tumor classification using MRI has developed significantly from early computer-aided image-processing and handcrafted-feature methods to conventional machine learning, deep CNNs, transfer learning, EfficientNet, Vision Transformers, and hybrid CNN–Transformer systems.

The reviewed studies show promising results across different datasets and classification settings, but reported performance cannot be interpreted independently of dataset composition, preprocessing, class distribution, and validation strategy.



Limited external validation, dataset diversity, explainability, reproducibility, and clinical integration remain important challenges.

Future studies should therefore emphasize robust generalization, interpretable models, diverse multi-center data, independent validation, and human–AI collaboration.

Deep learning provides a strong research foundation for computer-aided MRI analysis, but additional validation is needed before such systems can be incorporated responsibly into routine clinical decision-support workflows.

TABLE I
COMPARATIVE ANALYSIS OF REPRESENTATIVE MRI BRAIN TUMOR CLASSIFICATION STUDIES (2000–2026)

Author & Year	Method	Dataset / Setting	Key Findings
Early studies (2000–2008)	Image processing / CAD	MRI; early automated analysis	Established foundations in segmentation, feature extraction and computer-aided tumor analysis.
Zacharaki et al. (2009)	Texture/shape features + SVM	102 histologically diagnosed brain tumors	SVM-based classification supported tumor type and grade analysis; multiple performance measures reported.
El-Dahshan et al. (2014)	PCNN + DWT + PCA + BP-NN	101 MRI images	Reported 99% classification accuracy for normal/abnormal classification in the evaluated dataset.
Sharma & Marikkannu (2015)	3D MRI + RGSA + SVM	3D MRI; benign vs malignant	Explored a hybrid feature/classification framework for brain tumor MRI analysis.
Fabbri et al. (2017)	Fully connected NN + CNN	3,064 CE-MRI images; 3 tumor types	Best trained network reported 91.43% average five-fold cross-validation accuracy.
Deepak & Ameer (2019)	GoogLeNet transfer learning	Figshare MRI; 3 classes	Reported 98% mean accuracy using patient-level five-fold cross-validation.
Tandel et al. (2020)	AlexNet transfer-learning CNN	2–6 class multiclass settings	Reported mean accuracies of 100%, 95.97%, 96.65%, 87.14%, and 93.74% across settings.
Islam et al. (2023)	VGG19, InceptionV3, MobileNet, DenseNet121	4 classes; three benchmark datasets	MobileNet reported 99.60% accuracy in the stated experimental setting.
Zulfiqar et al. (2023)	EfficientNetB0–B4 + Grad-CAM	3 tumor classes	EfficientNetB2 reported 98.86% test accuracy with visual attention analysis.
Reddy et al. (2024)	Fine-tuned Vision Transformers + CNN baselines	7,023 MRI images; 4 classes	FTVT-L16 reported 98.70% accuracy; CNN baselines were also evaluated.
Goceri (2024)	CNN + Transformer blocks	Tumor classification + glioma grading	Reported 98.66% classification and 99.21%



			grading accuracy on evaluated datasets.
Bouhafra & El Bahi (2025)	Systematic review of ML/DL	Studies published 2020–2024	Highlighted transfer learning, autoencoders, transformers, attention mechanisms and recurring validation challenges.
Anand et al. (2026)	Optimized CNN + transfer-learning comparisons	3,264 images; 4 classes	Reported 98.5% accuracy for the optimized CNN in the evaluated setting.
Abbas et al. (2026)	Custom CNN + pretrained models + ensembles	Public MRI datasets; multiclass	Compared individual pretrained models and ensemble configurations; model-specific results require the original study.

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