

# Brain Tumor Detection and Classification: A Review of Deep Learning Techniques and Clinical Applications

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**Abstract:** Among the most complicated and life-threatening neurological diseases are brain tumors, which need for early and precise diagnosis to enhance patient outcomes. Though manual interpretation is laborious, subjective, and vulnerable to human error, medical imaging techniques including MRI, CT, PET, and DWI are essential for identifying and categorizing brain cancers. Recent developments in artificial intelligence (AI), especially deep learning (DL), have made it possible to create strong computer-aided diagnostic (CAD) systems that can automatically identify, categorize, and segment brain tumors with great accuracy, therefore overcoming these constraints. Designed for brain tumor analysis, this study offers a thorough assessment of state-of-the-art DL-based methods—including convolutional neural networks (CNNs), Vision Transformers (ViTs), hybrid CNN-transformer models, and IoMT-integrated systems. The survey methodically assesses every approach in relation to architecture, feature extraction techniques, classification performance, and clinical relevance. It also points out important issues in the discipline like data asymmetry, restricted interpretability, variation between imaging modalities, and lack of generalizability on external datasets. Each approach's benefits, limitations, and real-world possibilities are emphasized by means of a methodical comparison study. This work intends to steer future research toward constructing more accurate, efficient, and explainable AI-driven brain tumor detection systems able of integration into clinical workflows by means of identification of current research gaps and practical recommendations.

**Keywords:** Brain Tumor Diagnosis, Deep Learning (DL), Convolutional Neural Networks (CNNs), Vision Transformers (ViTs), Computer-Aided Diagnosis (CAD)

## I. INTRODUCTION

The central nervous system of the organism conveys sensory data and related activities. The spinal cord and brain spread this knowledge. The brain's three main parts are the cerebrum, cerebellum, and brainstem. Weighing between 1.2 and 1.4 kg, the average human brain has a volume of 1260 cm<sup>3</sup> for males and 1130 cm<sup>3</sup> for females. [1] Judgment, motor control, and problem-solving skills are all under the frontal lobe of the brain. Body posture is controlled by the parietal lobe. While the temporal lobe controls memory and hearing, the occipital lobe handles visual processing. Gray cortical neurons make up the cerebral cortex, the outermost layer of the cerebrum [2]. The cerebellum is rather smaller than the cerebrum. Its purpose is motor control, the methodical management of voluntary movements in creatures with a brain system. The ALI, lesionGnb, and LINDA techniques ignore the little lesion region because of their varying sizes and stroke areas. Unlike other animals, humans have a very sophisticated and structured cerebellum. The cerebellum is made up of three lobes: anterior, posterior, and flocculonodular. A circular form known as the vermis links the anterior and posterior lobes. The cerebellum is made up of a thin gray cortical layer somewhat thinner than that of the cerebrum and an inner white matter (WM) region. Complex motor activity coordination is aided by the anterior and posterior lobes. The flocculonodular lobe controls the body's equilibrium. A pair of as its name implies, the

brain stem is a 7- to 10-centimeter-long structure resembling a stem. Apart from many other vital tasks like breathing, it controls and directs eye movements, balance, and maintenance. [3] Moreover, it has bundles of cranial and peripheral nerves. From the thalamus of the cerebrum to the spinal cord, the neural pathways go over the brainstem. They then spread all throughout the body. The brainstem's main components are the medulla, pons, and midbrain. The midbrain helps in muscular, auditory, and visual processing as well as eye movement control. While the medulla oblongata controls blood flow, swallowing, sneezing, and other processes, the pons mediates sensory perception, inter-brain communication, and breathing.

Brain tumors classified as indolent or aggressive [4] While a malignant tumor, recognized for its aggressive behavior, spreads from one site to another, a benign tumor does not infiltrate neighboring tissues. Brain tumors are graded by the WHO as I–IV. While grades III and IV cancers show increased aggressiveness and a worse prognosis, grades I and II tumors are thought to develop slowly. This describes the particularity of brain tumor grading in this setting.

**Grade I:** These tumors develop slowly and don't spread fast. They are connected to improved long-term survival results and may be completely removed by surgery. Grade 1 pilocytic astrocytoma is one such malignancy.

**Grade II:** Though they can spread to other organs and advance into higher-grade cancers, these tumors show moderate growth. These tumors might come back after surgery. Oligodendroglioma is a kind of tumor.

**Grade III:** These tumors can spread to nearby tissues and develop faster than grade II malignancies. For some cancer kinds, surgery by itself is inadequate; adjuvant chemotherapy or radiation treatment is advised. Anaplastic astrocytoma is a prime example of this sort of cancer.

**Grade IV:** The most aggressive and most spreadable tumors are these. They could even develop quickly via blood vessels. One such kind of tumor is glioblastoma multiformed.

- **Ischemic stroke:** A major worldwide source of death and handicap is the aggressive brain disease known as ischemic stroke. When the cerebral blood flow is disrupted, an ischemic stroke results in underperfusion, tissue hypoxia, and necrosis within hours. Based on their length, stroke lesions are classified into several phases: acute (0–24 hours), sub-acute (24 hours–2 weeks), and chronic (after 2 weeks).
- **Brain imaging modalities:** Widely utilized to examine the brain anatomy are three main techniques—PET, CT, DWI and MRI.
- **Positron emission tomography:** Positron Emission Tomography (PET) uses a particular kind of radioactive tracer. Including blood flow, glucose metabolism, lipid synthesis, oxygen consumption, and amino acid metabolism, positron emission tomography (PET) assesses metabolic characteristics of brain tumors. Using fluorodeoxyglucose (FDG), the top nuclear medicine, it remains among the most effective metabolic approaches. In brain imaging, FDG is a frequently used PET tracer. FDG-PET scans, however, have many drawbacks including the inability to differentiate between a recurrent high-grade tumour and necrotic radiation. Moreover, a PET scan might subject someone to radioactive tracers that could harm the body and cause an allergic response after the operation. Some people are sensitive to aspartame as well as iodine. Furthermore, PET tracers cannot exactly identify anatomical regions [5–6] of their relatively low spatial resolution compared to MRI images.
- **Computed tomography:** Compared to traditional X-ray pictures, computed tomography (CT) scans offer more comprehensive information. CT scans have been extensively suggested and utilized since its beginning; a research indicated that 62 million CT scans were conducted yearly in the United States alone, with 4 million of those scans being for children. CT scans show the soft tissues, blood vessels, and bones of several human body parts. CT scans release more radiation than traditional X-rays; the related cancer hazards have been assessed depending on CT radiation exposure [7]. MRI can even assist in assessing structures concealed by CT scan, providing excellent contrast among the soft tissues, and provides a clearer anatomical structure.
- **Magnetic resonance imaging:** An MRI scan is used to completely analyze different bodyparts, and it also helps to detect abnormalities in the brain at earlier stages than other imaging modalities. Hence, complex brain structures make tumor segmentation a challenging task. This review discusses preprocessing approaches, segmentation techniques, feature extraction and reduction methods, classification methods, and deep learning approaches. Finally, benchmark datasets and performance measures are presented [8].



- **Diffusion weighting imaging:** MRI sequences are used to examine the stroke lesions depending on the many criteria like age, location and extent areas. A computerized approach might be used in the context of treatment to precisely diagnose the pace of illness development. Often working on studies connecting brain deficits to cognitive function, the cognitive neuroscientists. They noted that a key duty to examine the whole infected brain area supporting the therapy process is segmentation of the stroke lesions. But, stroke appearance changes with time, making segmentation of the stroke lesions a challenging process. Stroke lesion identification uses the MRI sequences FLAIR and diffusion weighted imaging (DWI). In acute strokes stage, DWI sequence emphasizes the infected area as a hyperintensity. The under perfusion area is the mapping amplitude of the perfusion [9]. The dis-similarity between two areas might be seen as penumbra tissue. Stroke lesions show in different sites and forms. Different kinds of lesions show in a range of size and form; these lesions are not in line with vascular patterns and more than one lesion might show at the same time. The stroke lesion size ranges in diameters from a few millimeters to a complete hemisphere. The structure of the hemisphere is different, and its intensity might greatly change inside the afflicted area. Moreover, the comparable look of the disease including white matter hyperintensities and chronic stroke lesions [10] makes automated stroke segmentation challenging.

### Challenges

- **Limited Availability of Labeled Medical Data:** High-quality, annotated datasets for brain tumors are scarce due to privacy concerns, cost of labeling, and complexity of medical diagnosis, limiting model training and generalization.
- **Data Imbalance Among Tumor Types:** Brain tumor datasets often contain unequal representation of tumor classes (e.g., more gliomas, fewer pituitary tumors), leading to biased predictions and poor performance on underrepresented classes.
- **High Intra-Class Variability and Inter-Class Similarity:** Tumors of the same class may differ significantly in appearance, while different types may appear visually similar, making classification a complex task for both traditional and deep learning models.
- **Interpretability and Explainability of Deep Learning Models:** Many deep learning models function as “black boxes,” offering little insight into decision-making processes. This lack of interpretability limits trust and clinical adoption of AI-assisted systems.
- **Variability in Imaging Modalities and Acquisition Protocols:** Differences in MRI scanners, image resolution, and acquisition parameters across institutions can degrade model performance and hinder cross-site applicability.
- **Computational Complexity and Resource Requirements:** Advanced models like transformers and 3D CNNs require high computational power, memory, and processing time, which limits their deployment in real-time or resource-constrained clinical settings.
- **Integration with Clinical Workflow:** Even high-performing models often lack the flexibility or user interface integration needed to be easily adopted into hospital radiology systems or electronic medical records.
- **Robustness to Noise and Artifacts:** MRI images may contain noise, motion artifacts, or distortions due to patient movement or scanner limitations, which can negatively affect segmentation and classification accuracy.
- **Cross-Dataset Generalization:** Models trained on one dataset (e.g., BraTS) may perform poorly on others due to domain shift, highlighting the need for domain adaptation and robust transfer learning approaches.

### Motivation and contribution

Brain tumors pose a serious threat to human health due to their complex nature, rapid progression in high-grade forms, and the challenges associated with early and accurate diagnosis. Traditional diagnostic approaches often fall short in detecting tumors at early stages or in differentiating between tumor types due to the subtle differences in medical

images. Moreover, manual analysis of brain imaging is time-consuming, prone to errors, and requires expert radiological interpretation. With the advent of deep learning and advanced imaging techniques, there is a growing opportunity to automate and enhance brain tumor detection through computer-aided diagnosis systems. However, existing models still face challenges such as data imbalance, limited interpretability, and insufficient generalizability across datasets. This motivates the need for developing more accurate, robust, and explainable AI models that can assist radiologists in early detection, grading, and classification of brain tumors. Integrating advanced neural networks, transformer architectures, and hybrid learning approaches can significantly improve diagnostic accuracy, reduce manual burden, and support better clinical outcomes.

- **Extensive Literature Survey on AI-Based Brain Tumor Classification:** This work presents a comprehensive survey of state-of-the-art methods used for brain tumor detection and classification, covering a diverse range of models including CNNs, Vision Transformers (ViTs), hybrid CNN-Transformer architectures, and IoMT-integrated CAD systems. The paper highlights recent trends, techniques, and performance metrics across major datasets like BRATS2018/2019 and BraTS-21.
- **Systematic Comparison with Gaps and Performance Insights:** The survey systematically analyzes each method in terms of feature extraction strategy, classification accuracy, advantages, and limitations. It also identifies key research gaps—such as lack of dataset transparency, limited model interpretability, generalizability across datasets, and high computational complexity—providing a structured comparative view of current solutions.
- **Strategic Future Directions and Clinical Applicability Guidance:** Based on the insights from the reviewed models, the paper offers practical recommendations for future research. These include improving cross-dataset robustness, incorporating interpretable AI for clinical trust, optimizing architectures for real-time and low-resource deployment, and designing integrated multi-modal systems for enhanced diagnostic precision.

## II. RELATED WORK

Using a new feature selection technique termed CVM, this paper presents a CAD system for categorizing high-grade malignant brain tumors into five different categories. Based on chosen characteristics, it uses a wide feature set spanning six domains and assesses three classifiers—KNN, mSVM, and NN. Proving the method's efficacy, the NN classifier attained the greatest accuracy at 95%, indicating gains of 2–4% above current ICA and GA-based techniques [11]. This paper presents a CADx system for diagnosing stomach diseases utilizing Xception CNNs with data augmentation and CAM-based visualization, hence addressing data scarcity in medical imaging. By overlaying lesions on normal photos, CAM improves the dataset by highlighting areas of interest. Using F1/AUC scores and confusion matrices, evaluation reveals better performance and indicates the system's promise in low-data settings [12]. Using texture, intensity, and form characteristics chosen by a MAP-based firefly algorithm, a hybrid ML system is suggested. With an F-score of 0.91 for tumors and 0.99 for strokes, the HSVFC classifier beats other models with 99.2% accuracy for brain strokes and 88.3% for brain tumors. Compared to conventional classifiers, it shows better categorization with few false positives [13]. Using colorful tissue modeling and the firefly optimization process, this work improves tumor location. Though the dataset information is sparse, it performs very well (96.47%), sensitivity (96.32%), and specificity (98.24%). While showing good findings in tumor identification, the study emphasizes the necessity of improved dataset clarity, cross-dataset assessments, and interpretability [14]. This work classifies brain MRIs by extracting and assembling top-performing deep features using pre-trained deep neural networks (DNNs). Although it lacks comparisons with other DL medical models and excludes thorough metrics, it performs well across three available datasets. The paper underlines future research's requirement for explainable artificial intelligence and consistent assessment [15].

Brain tumor classification on unbalanced data is done using a deep transfer learning strategy fine-tuning DenseNet201. The average pool layer extracts feature; EKbHFV and MGA are two selection methods shown. Although the paper lacks information on dataset characteristics and preparation, it scores more than 95% accuracy on BRATS2018 and BRATS2019 datasets. More research is required to evaluate the generalizability for clinical application, hyperparameter influences, and feature selectors [16]. Using RESTNET 5.0 with transfer learning, another study on

brain tumor detection finds 96% accuracy. Although the work shows good classification potential on its dataset, it does not specify a clear research gap even if it emphasizes advances over six current ML models for diagnosing glioma, meningioma, and pituitary cancers [17]. Deep learning-based categorization is employed in a study concentrating on early brain tumor identification utilizing 2D MR images. Although the study lacked clarity on the particular issue addressed, it attained a high 99.39% accuracy by means of 10-fold cross-validation. It asks for finding the best mixes of classifiers and feature extractors to improve system performance [18]. Another method classifies tumors into glioma, meningioma, and pituitary types using GoogleNet-based transfer learning combined with IoMT. Its F1 score is 0.969, it has 96.6% specificity, and it has 96.9% accuracy. Emphasizing the benefits of merging deep learning with IoMT for real-time medical applications, the study shows practical utility in early diagnosis by means of early diagnosis [19].

With individual and ensemble ViTs above 97% accuracy, Vision Transformers (ViT) are assessed for brain tumor categorization. Fine-tuning all parameters yields the best results—97.7%. Though misdiagnosis of meningiomas caused by feature overlap is observed, higher resolution input and hyperparameter adjustment help to improve results even more. The work shows ViTs are better than more conventional CNNs [20]. The LCDEiT paradigm is presented to solve data scarcity and computational inefficiencies in medical scanning. Achieving up to 98.11% accuracy and strong F1-scores across benchmark datasets, it blends external attention with a teacher-student structure. The model provides efficient and accurate performance for brain tumor classification in low-resource environments, effectively addressing present constraints [21]. Tumor extraction and classification are handled by the VS-BEAM model using a convolutional autoencoder. Although the work lacks data openness, comparisons with other techniques, and robustness tests, it reports 98% accuracy and 91% sensitivity across brain tumor classifications. Its clinical significance is encouraging, particularly in multi-class tumor categorization, nevertheless [22]. A thorough study describes how CNNs, CapsNets, and ViTs are used in brain tumor detection and suggests future paths include improving feature map quality and merging segmentation with classification. Among the recommendations are further in-depth study of activation functions, 3D network topologies, and advanced data augmentation to enhance CNN-based diagnostic tools [23]. Emphasized for their simplicity and efficiency in handling big datasets for image identification, Vision Transformers (ViT) are though more tuning and adaption for neuroimaging are still required, these models exceed CNNs in diagnostic performance when trained on enough data by processing input pictures as patches using conventional Transformer encoders [24]. Brain tumor categorization is suggested using a new hybrid deep learning model integrating CNNs and Transformers with FFM and IMM components. By means of a stronger and understandable system, the integration improves feature representation and classification accuracy, hence supporting radiologists in clinical decision-making. Using Walsh-Hadamard transformations, Gabor filtering, and Minkowski metrics, a CBMIR approach is shown for quick brain tumor image retrieval from MRI data. The system outperforms current techniques as wavelet and Hough transformations in accuracy and time economy. Future goals include improving scalability, MRI clarity, and compatibility with various tumor types. Combining spatial and channel attention blocks with a parallax attention module improves stereo imaging approaches for endoscopic diagnosis. By addressing low-resolution imaging problems typical in stereo endoscopy, the model trained on the da Vinci dataset increases PSNR and SSIM, hence supporting precise diagnosis in procedures like cardiology and GI therapies [18].

A CT-based research examines completely automated body composition (BC) analysis utilizing ResUNET, UNET++, and Ghost-UNET architectures across more than 4,000 CT images. UNET++ works best with a Dice score of 0.981. By simplifying the examination of organs and adipose tissues, this automation increases consistency and scalability in metabolic health risk evaluation. Because of their capacity to manage high-dimensional data, transformers are being used more and more in neuroimaging. With more accuracy and less computing cost, they beat CNNs in brain tumor segmentation and classification tasks. Still ongoing research topics, nevertheless, are issues like model interpretability, hardware costs, and data constraints [19]. A saliency-aware super-resolution (SR) model is finally put out to enhance stereo endoscopic imaging. The model surpasses current methods such as E-SEVSR and CCSBESR in clarity and structure preservation by use of cross-view interaction modules and feature improvement. In endoscopic operations, this development enables more exact surgeries and diagnoses [25].

Table 1: Survey table

Ref	Method	Advantages	Disadvantages	Research Gap
[18]	Self-supervised contrastive learning with unlabeled data	Uses unlabeled data; improves representation via contrastive loss	Lacks dataset and augmentation details	Impact of augmentation and pre-training configs unexplored
[19]	Dual Disentanglement Network (D2-Net) for MRI with missing modalities	Captures both modality-specific and tumor-specific features	No ablation studies or cross-dataset testing	Effect of missing modalities and generalizability
[20]	TD-CNN-LSTM model for multi-sequence MRI classification	Handles all four MRI sequences; high test accuracy (98.90%)	No comparison with other modern DL models	Need for broader benchmarking and optimization studies
[21]	Vision Transformer (ViT) ensemble	High accuracy with ensemble; robust across resolutions	Misclassification of meningiomas due to feature overlap	Scalability to other datasets and model simplification
[22]	LCDEiT with teacher-student model and external attention	Efficient; performs well on limited data; high F1-scores	Limited interpretability; complexity not evaluated	Model interpretability and application in resource-limited settings
[23]	VS-BEAM using convolutional autoencoder	Accurate extraction and classification of tumor regions	Lacks robustness testing and method comparison	Dataset transparency and multi-dataset validation needed
[24]	Transfer learning with ResNet50, DenseNet201, etc.	High accuracy using transfer learning across models	High model complexity; no research gap clearly addressed	Comparative evaluation with medical-specific models missing
[25]	Fine-tuned DenseNet201 with EKbHFV and MGA feature selection	Strong performance on BRATS2018/19 with >95% accuracy	No info on dataset characteristics or real-world deployment	Assessment of feature selection and clinical applicability needed
[26]	RESTNET 5.0 with transfer learning for tumor detection	Outperforms other ML models on 3 tumor types	Research gap not clearly defined	Clarify problem being solved and optimize model comparison
[27]	CNNs + Transformers + FFM/IMM hybrid for BTc	Enhanced feature representation and model interpretability	Computational complexity not addressed	Improve efficiency, clarity, and cross-model integration

### Research gap

- **Lack of Dataset Transparency:** Several studies fail to provide comprehensive details about the datasets used, including properties, pre-processing methods, and acquisition protocols, making reproducibility and validation difficult.
- **Limited Evaluation on Cross-Dataset Generalization:** Most models are tested on a single dataset (e.g., BRATS2018/19), and their performance on external or clinical datasets remains unknown, raising concerns about generalizability.
- **Insufficient Exploration of Data Augmentation Techniques:** Despite using augmentation, few studies analyze the effect of different augmentation types or configurations on model robustness and performance.

- **Absence of Comparative Benchmarks:** Some works lack comparisons with recent state-of-the-art models or do not conduct ablation studies to assess the contribution of specific components in their proposed architectures.
- **Overlooked Interpretability and Explainability:** Many high-performing models function as black boxes, providing little insight into decision-making, which limits clinical trust and practical implementation.
- **Handling of Imbalanced and Limited Data:** Models often struggle with class imbalance or limited sample sizes, especially for rare tumor types, and do not include mechanisms to effectively mitigate this issue.
- **Inadequate Hyperparameter and Threshold Analysis:** The impact of varying hyperparameters and threshold values in feature selection or classification is underexplored, leaving optimization potential untapped.
- **Scalability to Real-Time or Resource-Constrained Environments:** High-complexity models like Transformers and 3D CNNs lack assessment for computational efficiency, making their deployment in real-time or low-resource settings challenging.
- **Integration of Feature Selection with Deep Architectures:** Few models integrate automated or hybrid feature selection methods into deep learning pipelines, potentially limiting their ability to extract the most discriminative features.
- **Clinical Validation and Application:** There is limited discussion on translating models to real clinical workflows, including integration with PACS systems, radiologist tools, or actual patient diagnostic pipelines.

### III. CONCLUSION

Emphasizing the increasing influence of deep learning, transformer-based architectures, and hybrid AI models in medical image analysis, this paper offers a thorough account of current developments in the field of brain tumor classification. By means of a thorough comparison of several approaches—including CNNs, Vision Transformers, IoMT-enabled systems, and self-supervised learning techniques—this work has shown the promise of artificial intelligence in enhancing diagnostic accuracy, efficiency, and automation in clinical processes. Though much has been done, issues like data openness, model interpretation, computational difficulty, and restricted generalization still exist. The survey provides insightful analysis of future paths for creating more strong, scalable, and explainable brain tumor diagnostic systems by means of identification of important research gaps and evaluation of the benefits and drawbacks of each approach. Combining these smart models with real-time clinical decision support systems might change brain tumor diagnosis and patient treatment.

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