

AI in MRI brain tumor diagnosis: A systematic review of machine learning and deep learning advances (2010–2025)

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ABSTRACT

Brain tumors present critical health challenges due to abnormal tissue growth within the brain, potentially leading to life-threatening conditions if left untreated. MRI stands as the primary diagnostic tool for identifying brain tumors, offering superior resolution and tissue differentiation compared to other imaging modalities. This systematic literature review explores the application of ML and DL techniques in enhancing the diagnosis of brain tumors from MRI scans. ML and DL algorithms, particularly CNNs, have demonstrated significant success in automating the detection and classification of brain tumors by analyzing complex imaging patterns. The review follows PRISMA guidelines, synthesizing findings from studies between 2010 and 2025. Key themes include the utilization of diverse datasets, advanced feature extraction methods, and the computational efficiency of ML and DL models. Despite notable advancements, challenges such as data diversity and model interpretability persist, underscoring the need for ongoing research to optimize these techniques for enhanced clinical outcomes in brain tumor diagnosis. The review discusses the effectiveness of CNNs, SVMs, ensemble methods, transformers and other ML approaches in improving diagnostic accuracy and reliability. It also addresses future research directions aimed at overcoming current limitations and advances in the field.

1. Introduction

Artificial intelligence (AI) has a major impact on medical imaging, especially in brain tumor segmentation and diagnosis via MRI scans. Yet, the literature tends to make the same observations regarding AI effectiveness without critically evaluating clinical usability, ethical issues, and generalizability problems. While previous reviews primarily evaluate individual algorithms or performance measures, they rarely offer a global view that bridges technical progress with practical use. Brain tumors are solid neoplasms that form within the skull and are the result of aberrant cell division that is not under control [1,2]. Even though they frequently originate in the brain, these lesions can also develop in the brain envelope, cranial nerves, lymphatic tissue, and blood vessels [3]. Additionally, brain tumors may arise as a result of the metastasis of malignancies from other regions of the body [4]. The classification of brain tumors is based on various factors, including their location, the type of tissue from which they originate, and whether they are

malignant or benign [5,6]. Primary brain tumors are termed after their cell type [7]. These tumors may be benign, which means they don't spread to other bodily organs; an example is meningioma. High-grade anaplastic astrocytoma is prevalent [8–11]. Secondary brain tumors, sometimes called metastatic or malignant tumors, are caused by cancer cells that move to the brain [12–14]. These tumors usually come from kidney, lung, breast, or skin melanomas. Brain scans, particularly MRI, are crucial for visualizing the internal anatomy of the brain. MRI provides an unparalleled view inside the human body, making it a valuable tool in the diagnosis and classification of brain tumors [15]. In many studies, supervised and unsupervised algorithms have classified MR images normal or abnormal [16].

Effective brain tumor treatment and patient outcomes need early diagnosis [17–19]. These tumors cause brain cell growth and damage that can impair brain function [20]. MRI has become the primary modality for brain tumor detection due to its superior imaging capabilities compared to other techniques such as CT scans [21,22]. MRI's

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high-resolution images reveal complicated brain structures, for tumour identification and research [23,24]. MRI imaging uses T1, T2, T1-CE, and FLAIR sequences, each offering unique advantages for tumor detection and characterization [25,26]. Among these, T1-weighted contrast-enhanced imaging is particularly effective in delineating tumors from surrounding healthy tissues [27,28]. The difference between benign and malignant tumors, of which there are over 200 types, further complicates diagnosis and treatment [29]. The American Cancer Society highlights that untreated brain tumors can severely impair brain function and are often fatal [30]. The increasing mortality rates associated with brain tumors underscore the urgency for improved diagnostic methods [31]. ML and DL technologies have shown promising advancements in medical imaging, enhancing the diagnostic process through automated pattern recognition and classification [32,33]. These techniques leverage complex algorithms to analyze MRI scans with high precision, potentially reducing the reliance on manual examination by experts. CNNs, which are able to learn and recognize detailed patterns from big datasets, are particularly useful for processing medical pictures [34–36]. This is because CNNs are able to learn and recognize intricate patterns. CNNs have shown highly effective in a variety of image processing tasks, including tumour identification and classification [37,38]. In addition to CNNs, other DL methods such as autoencoders have been employed for unsupervised representation learning, contributing to improved diagnostic accuracy [39–42]. The application of DL extends beyond brain tumor detection to other medical conditions, such as lung cancer and cardiovascular diseases, showcasing its versatility and effectiveness [43,44]. Medical imaging AI advancement could transform diagnosis and patient treatment [45–49]. Though there have been some reviews of AI methods for MRI-based brain tumor diagnosis, they tend to emphasize particular algorithms, performance on datasets, or segmentation accuracy without tackling more general challenges like generalizability, interpretability, and real-time feasibility in the clinic. This review differs from previous studies by offering a comprehensive overview of AI-based brain tumor diagnosis, highlighting the most important research gaps that impede its clinical adoption. Diverging from most of the earlier analyses, which primarily concentrate on algorithmic performance measures, this review discusses the limitations of current AI models in terms of handling variability in data, domain adaptation, and ethical considerations of bias in MRI data. This review also emphasizes the importance of explainability in AI decision-making, which has been poorly addressed in previous reviews. By systematically examining these limitations and outlining avenues for future research, this review aims to bridge the divide between progress in AI and its implementation in real-world clinical practice. The findings outlined here are a blueprint for the construction of stronger, explainable, and clinically feasible AI models of brain tumor diagnosis.

1.1. Motivation for this survey

The diagnosis of brain tumors by MRI is a vital medical endeavor that significantly impacts patient outcomes. Despite medical imaging advances, brain tumor detection remains difficult for healthcare providers. ML and DL have demonstrated substantial potential in automating and enhancing diagnostic processes in medical imaging. This survey reviews the use of these advanced approaches in brain tumor identification using MRI scans, highlighting gaps and suggesting further research.

1.2. Contributions of this survey

- A systematic review of ML/DL approaches (2010–2025) for MRI-based brain tumor diagnosis.
- A comparative benchmarking of CNNs, SVMs, and attention-based architectures, including Vision Transformers.
- An in-depth evaluation of computational complexity and real-time feasibility.

- A discussion on interpretability techniques (e.g., SHAP, Grad-CAM) for clinical AI models.
- Identification of research gaps, including federated learning and multi-modal imaging.

This research aims at improving AI techniques by incorporating more recent technologies such as CNN, Vision Transformers (ViTs), hybrid architectures CNN-SVM, and Generative Adversarial Networks (GANs) as opposed to traditional CNN based ones. Reviews done earlier rely heavily on single-model focus type systems, this study will be the first to concentrate on the intercomparison between federated systems and multi deep learning and machine learning models and their clinical significance through a benchmarking comparison table. Also, while past studies center on deep learning as a big umbrella, this review covers federated learning as an AI privacy sensitive multi institutional solution to the data privacy problem.

The other important component of this study is the application of multi-modal imaging like the combination of MRI and CT or PET to enhance the classification accuracy of tumors. This area have deeper delve into MRI segmentation but lacked in combining these techniques with other advanced imaging methodologies. In contrast to past reviews that focus on reporting the accuracy of models, this study takes a step further to demonstrate how in addition to the use of SHAP, Grad-CAM, and LIME to explain AI-driven diagnostics. Table 1 discusses about research gap found in the existing survey and how it could be addressed.

1.3. Organization of this survey

The survey follows PRISMA principles for a structured and comprehensive search. The methodology section includes a detailed article selection flowchart, which illustrates the systematic literature review process. This flowchart outlines the step-by-step procedure for identifying and selecting relevant studies. The survey includes and excludes works from 2010 to 2025 that use ML and DL to diagnose brain tumors from magnetic resonance images. The materials and methods section provides a thorough explanation of the search strategy and the criteria used for shortlisting articles, thereby ensuring transparency and reproducibility of the review process. Fig. 1 shows the reading map for this survey.

2. Methodology

The PRISMA guidelines for systematic reviews and meta-analyses were followed for this systematic literature review on brain tumor diagnosis using MRI and classification using ML and DL to ensure

Table 1
Identified research gaps and proposed optimization framework.

Research Gap in Existing Reviews	How This Study Addresses It
No focus on newer AI methods (ViTs, hybrid models)	In depth Validation of CNNs Vision Transformers and also hybrid model
No bench marking by comparing ML/DL models	Systematic comparison table tabulating accuracy, size of training data-set and computational cost
In perusing literature there was little to mention on federated learning for privacy preserving MRI analysis	Highlights federated learning in multi-hospital AI collaboration
Surprisingly zero effort in employing multi-modal imaging analysis (MRI + CT/PET)	Assessing the feasibility of multimodal AI for improved classification
Not much Exploratory analysis with all of the interpretability techniques	Discussion on SHAP, Grad-CAM, and other XAI methods for clinical trust
No examination of computational complexity for real-time implementation	Evaluation of computational costs and optimization strategies for deployment
Computational costs	Addressed AI biases, clinical validation hurdles, and HIPAA/GDPR compliance
Limited discussion on ethical concerns and regulatory challenges	

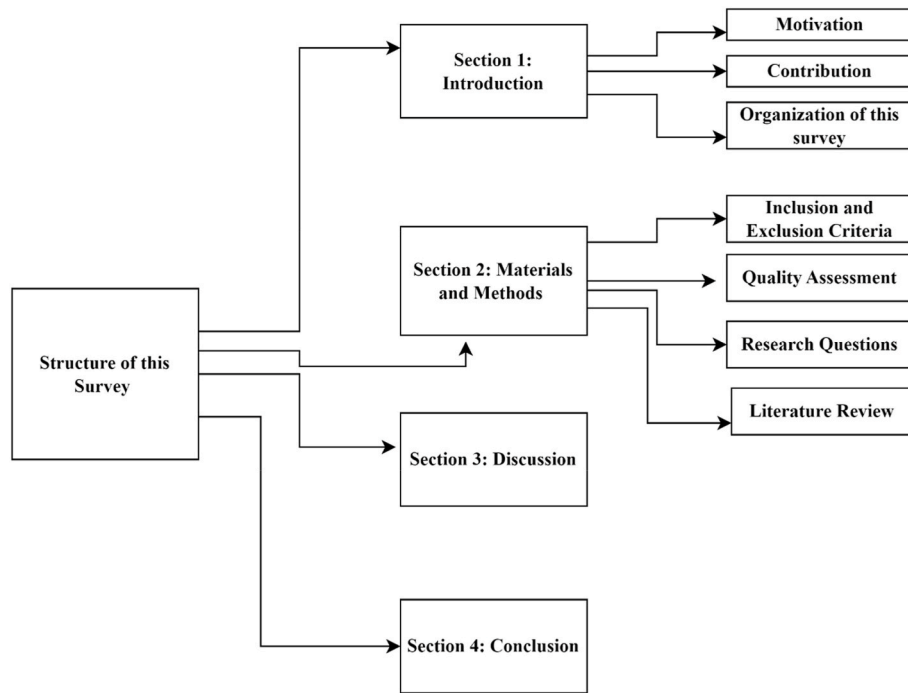


Fig. 1. Survey paper structure and components.

comprehensive coverage and methodological transparency. Because this is a systematic review, it follows the guidelines laid down by PRISMA on the conduct of systematic reviews and meta-analyses. A structured method of data extraction was thus considered in identifying, extracting, and analyzing key data items from each identified study in this review. A narrative synthesis was used to summaries data from included papers, highlighting trends, problems, and possibilities in machine learning and deep learning for brain tumor diagnosis using magnetic resonance images. The article selection flowchart that was utilized in the systematic literature review is depicted in Fig. 2. This flowchart outlines the step-by-step process employed to identify and select relevant articles.

In establishing our inclusion and exclusion criteria (detailed in Table 1), we focused on articles spanning the period from 2010 to 2025. The systematic review on machine learning and deep learning in brain tumor diagnosis using magnetic resonance images used a comprehensive search method to find relevant studies. Electronic databases including PubMed, IEEE Xplore, ScienceDirect, and Google Scholar were systematically searched using relevant keywords such as "Brain Tumor Diagnosis," "Magnetic Resonance Imaging (MRI)," "Diagnostic Accuracy," "machine learning," "deep learning," "transformers". Table 2 gives the summary table of selected studies on Brain tumor detection & classification. Table 3 gives an overview of inclusion and exclusion criterion used for shortlisting articles. A search technique for terms related to diagnosis of brain tumor from magnetic resonance images is shown in Table 4.

Comprehensive summary table incorporating all selected studies on **brain tumor detection and classification**, following **PRISMA guidelines**.

2.1. Research questions

One of the most integral components in the review paper is the development of a research question. The question will help set the scope and focus for the literature review. A well-written research question guarantees that the review will be structured, comprehensive, and relevant to the subject being investigated. A well-developed research question can facilitate identification and selection of the articles for review. This would limit the chances of biases during the selection

process and therefore ensure the comprehensiveness of the review as being representative of available literature. The major aim of the research is to give a broad overview of modern techniques used for brain tumor segmentation by using deep learning, Machine Learning and Vision Transformers. Table 5 gives the major research questions and objectives that have been reviewed in this review paper.

2.1.1. Study selection

A systematic search was carried out in the electronic databases of PubMed, IEEE Xplore, and Science Direct based on a set of keywords related to the diagnosis of brain tumors, MRI, machine learning, and deep learning. Based on the inclusion criteria, 155 studies were selected for this review.

2.1.2. Data extraction

The following data items were extracted from each study according to the PRISMA checklist (items 10a and 10b): Study Characteristics: Authors name, Year of Publication, Study Design, Sample Size, Type of Brain Tumor, Dataset, Details about the methodology, MRI Sequences Used, Feature Extraction Techniques, Algorithms used for tumor classification, Performance Metrics.

2.1.3. Data synthesis and analysis

Following the data extraction, a narrative synthesis of the findings of the identified studies and the trends in the application of ML and DL techniques in brain tumor diagnosis was made. To this end, the synthesis focused on Feature Extraction and Classification Trends, Review of feature extraction methodologies and classification algorithms of the studies mostly deep learning models focus on CNNs, Residual Networks, etc. Comparison of performance metrics like accuracy, sensitivity, Dice score among the studies in order to outline the most effective method for brain tumor detection is carried out in the survey.

2.2. Literature review

In the study [50], proposed a 3D MRI brain tumor segmentation approach. Their method introduces a novel technique for detecting tumors by identifying asymmetric patches within brain MRI images. In

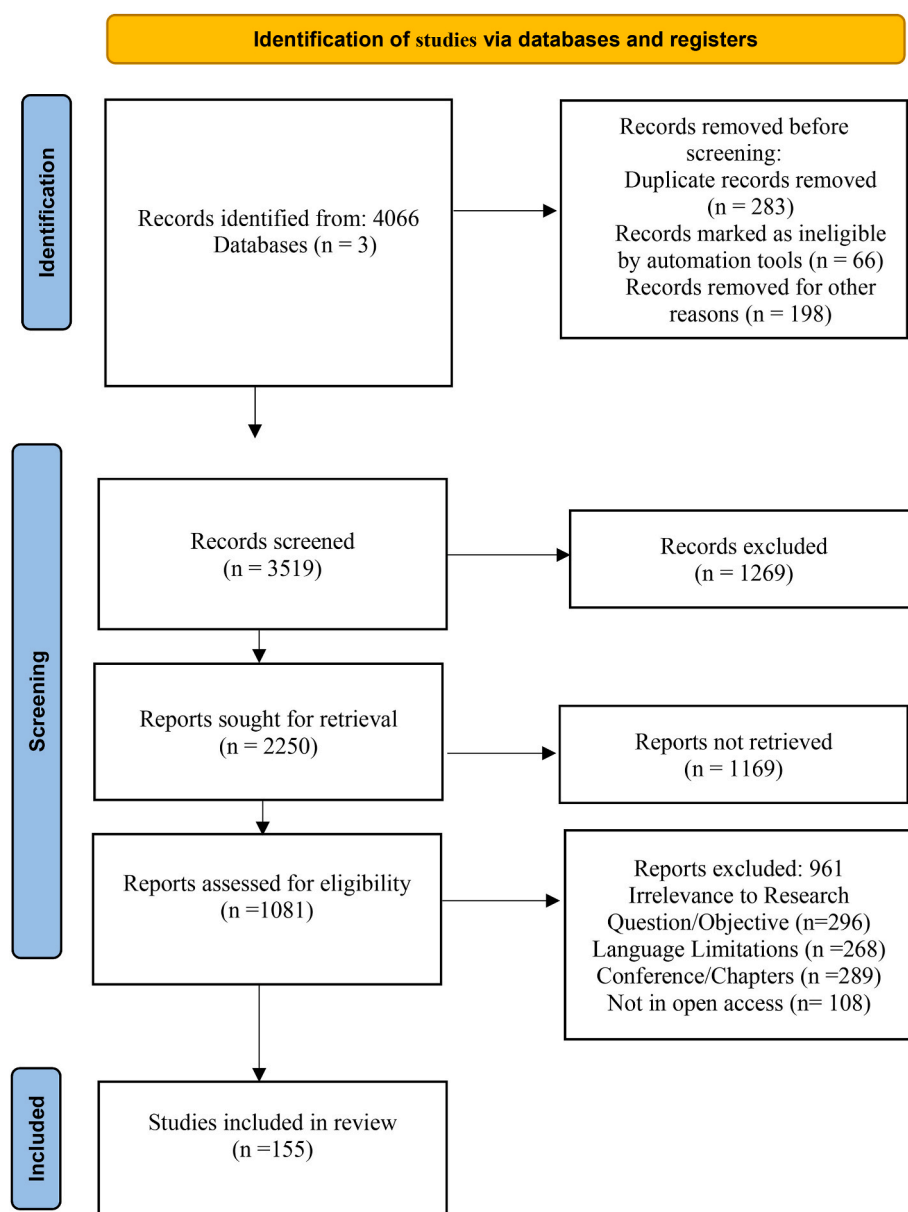


Fig. 2. Article selection flowchart for the systematic literature review.

study [51] uses MRI to diagnose patients. They use fuzzy connectivity, feature extraction, and selection to segment and classify normal and abnormal brain cases. In study [52] suggested a neural network to identify MR pictures as normal or abnormal. The Wavelet transform and principal component analysis classified 66 images with 100 % accuracy. In study [53] used the GLCM and a Sequential Forward Selection algorithm to distinguish normal and abnormal MR images using texture features and SVM. In study [54], statistical traits and a fuzzy SVM classifier diagnosed brain tumors with 95.80 % accuracy. In study [55] used image processing and classifiers like BPNN and K-NN to detect brain tumors using texture features like GLCM. In study [56] used diffusion-weighted imaging with thresholding and rule-based classifier to detect and categorize brain cancers into four kinds with varying accuracy. In study [57] used the best of six CNN models to classify benign tumor slices from MRI brain volumes with 96 %–99 % accuracy. In study [58] used Capsule net to classify three brain cancers and found that data pre-processing improves its performance. In study [59] developed a CNN model using hyper column method and pre-trained networks like Alex Net and VGG-16, obtaining 96.77 % accuracy in brain tumor MRI

classification without handcrafted features. In study [60] developed the Brain MR Net model, which outperformed pre-trained CNN models with a 96.05 % classification success rate, using attention modules and the hyper column approach for brain tumor identification. In study [61] used Residual Networks to classify brain tumor types with 99 % accuracy on a benchmark dataset. In study [62] used CNN to detect and classify brain tumors using an automatic segmentation and feature extraction technique. In study [63], CNN and thresholding automatically extracted and classified brain tumors in MRI images, with RMSprop optimizer performing best. In Ref. [64], ELM-LRF classification and image processing for cancer region extraction detected 97.18 % of tumors. The study [122] puts forward a new hybrid solution that unites Grey Wolf and Stochastic Fractal Search (GWO-SFS) optimization algorithms with ensemble random forest regressors based on a pre-feature selection procedure Table 4 shown the literature review studies. A novel transformer-based GAN has been developed by Ref. [124] for brain tumor segmentation of multi-modal MRI with a U-shape generator in the form of transformer blocks with a multi-scale L1 loss-based CNN discriminator, and obtained stable results with BraTs datasets.

Table 2
Summary table of selected studies on Brain tumor detection & classification.

Author(s) & Year	Title	Study Type	Methodology	Key Findings	Relevance to Research
Sontheimer (2015) [1]	Brain Tumors	Book Chapter	Literature review	Overview of brain tumor types and mechanisms	Foundational reference for tumor pathology
Pereira et al. (2016) [23]	Brain Tumor Segmentation Using CNNs in MRI	Research Article	Convolutional Neural Networks (CNN)	CNN-based segmentation approach	Deep learning advancements in medical imaging
Pacal (2024) [18]	Swin Transformer for Diagnosing Brain Tumors in MRI	AI-based Study	Vision Transformer (Swin Transformer)	Transformer-based AI model for MRI analysis	Novel AI method For enhancing diagnosis
Zhang et al. (2021) [21]	Overview of Multi-Modal Brain Tumor MRI Segmentation	Review Article	Multi-modal MRI segmentation	Reviews various segmentation techniques	Advanced methods for tumor segmentation
Gupta et al. (2017) [51]	Tumor Classification and Segmentation of MR Brain Images	Research Article	CNN-based segmentation and classification	Uses deep learning for segmentation and classification	AI-based brain tumor segmentation
Amin et al. (2020) [84]	Brain Tumor Detection Using Long Short-Term Memory (LSTM) Model	Research Article	Long Short-Term Memory (LSTM)	LSTM-based learning for tumor detection	Advanced AI-based classification
Rehman et al. (2021) [85]	Microscopic Brain Tumor Detection Using 3D CNN	Research Article	3D Convolutional Neural Network (CNN)	Feature selection and 3D CNN-based classification	Enhancing accuracy in tumor diagnosis
Noreen et al. (2020) [86]	Deep Learning Model for Brain Tumor Diagnosis	Research Article	CNN with concatenation	Concatenation-based deep learning approach	Improves CNN performance for medical imaging
Hashemzahi et al. (2020) [87]	Brain Tumor Detection Using CNN and NADE	Research Article	Hybrid CNN-NADE model	CNN-NADE model for segmentation	Integrates deep learning with probabilistic modeling
Khan et al. (2020) [88]	Multimodal Brain Tumor Classification Using Deep Learning	Research Article	CNN with feature selection	Combines robust feature selection with CNNs	Machine learning in radiology applications
Banerjee et al. (2018) [100]	Brain Tumor Detection and Classification from MRI	Conference Paper	Convolutional Neural Networks (CNN)	Convolutional networks for multi-sequence MRI analysis	Advances in CNN for tumor imaging
Zhou et al. (2018) [101]	Holistic Brain Tumor Screening and Classification Using DenseNet & RNN	Conference Paper	DenseNet + Recurrent Neural Network (RNN)	Combines DenseNet and RNN for tumor classification	Hybrid deep learning approach for classification
Peng S et al. (2020) [102]	Multi-Scale 3D U-Net for Automatic Brain Tumor Segmentation	Research Article	3D U-Net architecture	Proposes a 3D U-Net for tumor segmentation	AI-based segmentation model
Grøvik et al. (2020) [103]	Deep Learning for Brain Metastases Detection in MRI	Research Article	CNN-based segmentation	AI-based segmentation and detection of brain metastases	Deep learning application in MRI analysis
Pan et al. (2025) [128]	VcaNet: Vision Transformer for 3D Brain Tumor Segmentation	Research Article	Vision Transformer + Spatial Attention	Uses transformers with spatial attention for MRI	Advances in transformer-based medical image analysis
Rasheed et al. (2023) [135]	Brain Tumor Classification Using CNN & Attention Mechanisms	Research Article	CNN + Attention Mechanisms	Integrates CNN with attention for classification	Improves accuracy of tumor classification in MRI
Wang et al. (2023) [140]	Vision Transformers for Multi-Modal Brain Tumor MRI Segmentation	Review Article	Vision Transformer	Reviews transformer-based MRI segmentation models	Highlights advances in AI-driven segmentation
Lyu & Tian (2025) [154]	MWG-UNet++: Hybrid Transformer U-Net Model for MRI Tumor Segmentation	Research Article	Hybrid U-Net Transformer Model	Introduces a hybrid U-Net transformer model	Enhances segmentation accuracy in medical imaging

Table 3
Inclusion and Exclusion criterion used for shortlisting Articles.

Parameters	Inclusion Criteria	Exclusion Criteria
Time Frame	Papers published from the year 2010–2025.	Papers published before 2010.
Language	English (or languages with available translations)	Articles in languages without available translations
Intervention	Application of ML and DL algorithms specifically for the diagnosis of brain tumors using MRI	Studies using other imaging techniques (e.g., CT, PET) or focusing on treatment rather than diagnosis
Study Design	Peer-reviewed systematic reviews, randomized controlled trials, observational studies, case-control studies.	Conference proceedings, editorials, and non-peer-reviewed articles.
Imaging Modality	MRI as the primary imaging modality	Studies using only CT, PET, or hybrid modalities
Algorithms	Studies utilizing DL,ML,Vision Transformer methods	Rule-based or traditional statistical analysis studies
Outcomes	Studies reporting segmentation/ classification metrics (e.g., accuracy, Dice coefficient)	Studies without quantitative performance metrics
Population	Studies involving human participants with brain tumors (pediatric, adult)	Animal studies or simulated data only

EfficientNet-based transfer learning method was designed for classification of brain tumors into glioma, meningioma, and pituitary types from CE-MRI images. EfficientNetB2 was fine-tuned and Grad-CAM used for explainability, which provided high test accuracy (99.06 %) and high precision, recall, and F1 scores and established the model’s capability

Table 4
Search strategy keywords.

Keywords		Keywords	
1	Deep Learning	4	Magnetic Resonance Imaging (MRI)
2	Machine Learning	5.	Diagnostic Accuracy
3	Brain Tumor Diagnosis	6.	MRI Segmentation

for brain tumor classification [130]. Brain IAC, learned from more than 48,000 brain MRIs, was developed to acquire universal representations for a wide range of medical imaging tasks. Through self-supervised learning and adaptation, it performs better than task-specific models particularly in low-data and high-complexity situations enabling AI to become more practical in clinical and multimodal imaging pipelines [131]. A new CNN-based methodology that integrated image improvement methods Gaussian blur sharpening and CLAHE was presented for brain tumor (glioma, meningioma, pituitary) classification and non-tumor condition. With high accuracy of 97.84 % and superior performance on core metrics, the technique surpassed several pre-trained networks and exhibited great generalization potential in supporting clinical diagnosis [133]. Table 6 shows the summary and critical evaluation of selected studies on Brain Tumor segmentation using Deep Learning, including datasets and performance comparison.

2.2.1. ML-BASED approaches in brain tumour diagnosis

ML techniques have become pivotal in brain tumor diagnosis, enhancing accuracy and efficiency in medical imaging analysis. By using SVM, decision trees, and deep neural networks, ML models can detect and classify tumors from MRI scans with high precision. These

Table 5

Major research questions and objectives that have been reviewed in this review paper.

Research Question	Objective
RQ1: What are some recent MRI-based technique developments, made during the last decade, that improve the segmentations and characterizations of brain tumors?	To identify and analyze new developments in MRI-based segmentation techniques, including new methods and technologies developed in the last decade.
RQ2: How do ML and DL models develop for brain tumor segmentation using MRI data?	It basically aims to investigate the progress of machine learning and deep learning-based methods for the segmentation of brain tumors regarding methodologies, architectures, and achievements over time.
RQ3: What are the challenges and/or limitations of ML/DL-based methods for brain tumor segmentation, and how are these challenges being addressed?	The main challenges and limitations of ML/DL-based methods, such as dataset bias, computational efficiency, and model interpretability will be discussed, and strategies put in place to overcome the issues.
RQ4: Which datasets and metrics are the most used in MRI-based brain tumor segmentation studies, and how do they influence the performance of models?	This survey aims to review the most used datasets and metrics related to MRI-based brain tumor segmentation and explores their impact on model performance and generalization.

approaches improve diagnostic outcomes by automating and refining the interpretation of complex imaging data. A three-class, binary Auto ML model was built to diagnose the principal forms of pediatric posterior fossa tumors based on typical pre-surgical MRI results [65]. An automated classification system using MRI scans from various databases was introduced in Ref. [66] for early brain tumor detection. The methodology involves pre-processing with Median Filter, 3x3 picture block conversion, texture feature extraction with Gray-Level Co-occurrence Matrix, classification, and segmentation. To identify brain regions impacted, optimal probabilistic fuzzy C-means method segregated the anomalous ones. In order to comprehend glioblastoma tumors (grade I to IV), the most lethal malignancy of the nervous system [67], employed ML algorithms and protein-protein interaction networks to analyses differentially expressed genes. ML algorithms and skull-stripped MRI fluid attenuated inversion recovery scans are used to localize brain tumors [68]. Text on-map images and texture maps are created using Gabor filter bank after noise removal. Segmenting text on-map pictures into super pixels extracts low-level features that are combined with region-level data. The final sections contain the classification results for synthetic LG, synthetic HG, and actual high grade (HG). ML classifiers are fed a fusion of characteristics to distinguish brain cancers [69]. Genetic algorithms choose the finest extracted features. The proposed strategy outperformed existing methods on various datasets. Table 7 shows various studies of ML Models in Brain Tumor Diagnosis.

Fig. 3 illustrates the distribution of machine learning algorithms utilized in brain tumor diagnosis. Each segment represents a distinct algorithm and its proportionate contribution to the overall diagnostic process. The most commonly employed algorithms include Artificial Neural Networks (ANN), Adaptive Clonal Particle Swarm Optimization combined with Neural Networks (ACPSO + NN), and Rule-based Level Set Support Vector Machines (SVM). In contrast, Extreme Learning Machine with Local Regressive Forest (ELM-LRF) and Random Forest contribute to a smaller extent.

2.2.2. DL-BASED approaches in brain tumours diagnosis

DL techniques have revolutionized brain tumor diagnosis by leveraging neural networks to analyze complex MRI images with high accuracy. CNNs and other DL models excel in automatically detecting and classifying tumors, significantly improving diagnostic efficiency and precision. Brain tumor MRIs are segmented and convolution increased recognition rate by fusing PCA derived and synthetically generated

features [83]. In Ref. [84] implies that radiologist can classify brain tumors more accurately with the provided strategy. An evaluation of a 3D-CNN brain detection model was conducted on the BRATS 2015, 2017, and 2018 challenge datasets [85]. The model had the greatest BRATS 2015 classification accuracy and comparable accuracy to other methods. Inception-v3 and DensNet201 multi-level features are concatenated with SoftMax to classify brain tumors [86]. DL and ML brain tumor categorization fared worse than concatenation-based DL. A DL-based hybrid architecture classified 708 meningiomas, 1426 gliomas, and 930 pituitary tumors from 233 patients using CNN and neural autoregressive distribution estimates on T1-weighted contrast-enhanced MR [87]. DL and robust feature selection were used to create an autonomous multi-modal brain tumor categorization algorithm [88]. The brain tumor recognition and classification system [89] uses fuzzy-C-means segmentation with super-resolution and CNN with ELM classification. Super-resolution improved this system's accuracy by 10 %. In Ref. [90], the basic CNN design with Resnet50, with 10 more layers added instead of the final 5 layers. Brain MR Net outperforms pre-trained CNN models such as Google Le Net, Alex Net, and VGG-16 on the same data set. DL-based brain tumor detection via seed growing segmentation was proposed [91]. Structure and textural data from multi-modal MR images (T1, T2, T1CE, and FLAIR) were integrated using a discrete wavelet transform with Daubechies kernel and a 23-layered CNN to discriminate normal and brain tumor regions [92]. Alex Net, Google Net, and VGG Net were used to identify and classify 708 meningioma, 930 pituitary, and 1426 glioma brain tumors [93]. These architectures were validated using fine-tune and freeze transfer learning. Whale and Harris Hawks algorithms were used to classify deep CNN-based brain tumors in Ref. [94]. Improved seagull optimization classifies 204 brain tumor MRIs of T1, T2, and FLAIR modalities as normal or tumorous [95]. After segmentation using grab cut approach, CNN model VGG-19 deep features and Local binary pattern and histogram orientation gradient are optimized using entropy [96]. Before feeding optimal features to glioma and healthy image recognition classifiers, they are fused into one vector. On BRATS challenge databases, this technique was separately tested [97]. In Ref. [134], a CNN-based model integrated with a hybrid attention mechanism was proposed for classifying brain tumors including glioma, meningioma, pituitary, and non-tumor cases—from MRI scans. Achieving 98.33 % accuracy and high precision, recall, and F1-score, the method outperformed several pre-trained models and demonstrated strong generalization for clinical diagnostics. A new deep CNN-based method proposed in Ref. [136] for glioma, meningioma, and pituitary tumor classification from MRI scans. In comparison to traditional datasets and in comparison to models such as VGG16, ResNet50, and InceptionV3, the model exhibited a high accuracy of 98.04 %, with excellent precision, recall, and F1-scores, reflecting excellent generalization and performance for clinical application.

Table 8 presents the several studies on DL Models in Brain Tumor Diagnosis.

Fig. 4 presents the distribution of DL techniques utilized in brain tumor diagnosis. The various techniques, including GRU, Attention-Gated GRU, Softmax activation with Inception v-3 Classifier, KNN, CNN, ConvNets, DenseNet, and Multi-Scale 3D U-Nets. The pie chart illustrates the performance distribution of each technique, highlighting that GRU, Attention-Gated GRU, and Softmax activation with Deep belief Network achieved the highest performance, each with a score of 9.6 %.

2.2.3. Systematic comparison of ML/DL models

In the interest of offering a systematic comparison between different machine learning (ML) and deep learning (DL) models, Table 9 contrasts them on important factors including accuracy, size of dataset, computational efficiency, and clinical relevance.

This comparison allows for a better understanding of the trade-offs between various models of AI and their application in real-world

Table 6

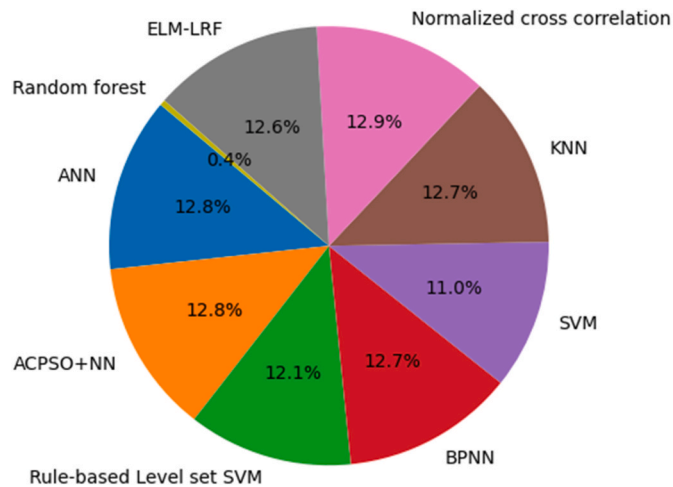
Summary and critical evaluation of selected studies on brain tumor segmentation using deep learning, including datasets and performance comparison.

Reference	Objectives	Feature Extraction	Techniques	Results	Conclusion	Remarks	Challenges Identified
Kermi, A., Andjough, K et.al (2018) [50]	Segment brain tumors in 3D MR Images.	Brain symmetry plane, fuzzy classification.	FBB	Average sensitivity of 81.59 % and 89.01 %	Effective in detecting tumors based on brain symmetry.	Advanced initialization may improve results further.	Difficulty in handling complex or asymmetric tumors.
Gupta, T., Manocha et.al (2017) [51]	Assist clinical diagnosis using MR imaging and spectroscopy.	Concentric circle technique, feature selection.	SVM	95 % accuracy, 100 % specificity, 90 % sensitivity	Demonstrates high accuracy in classifying brain tumors.	Redundancy in features is addressed through selection.	Requires better generalization to larger datasets.
Zhang, Y., Dong, Z et al (2011) [52]	Classify magnetic resonance images as either abnormal or normal by employing a neural network.	Wavelet transform, PCA.	KNN	100 % classification accuracy.	Highly accurate method for small datasets.	Larger dataset required to validate robustness.	Scalability to larger datasets remains untested.
Geethanjali, N., Pushpalatha. et at. (2023) [53]	Classify MR Images to normal and abnormal using texture features.	GLCM, Sequential Forward Selection.	SVM	Accuracy 99 %.	Demonstrates discriminative power of texture features.	Further research on feature selection methods needed.	Limited performance on multi-modal data.
Jayachandran, A. et al (2013) [54]	Detect brain tumors using a hybrid algorithm.	Anisotropic filter, PCA, texture features.	FSVM	95.80 % classification accuracy.	Combines statistical features and advanced classifiers.	May benefit from further optimization and simplification.	High computational complexity due to hybrid methods.
Gadpayleand, P., & Mahajani, P. S. (2013). [55]	Brain tumor detection system development and classification using image processing techniques.	GLCM, morphological operations.	K-NN	Accuracy 96.15 %	Demonstrates the utility of combining multiple classifiers.	Computational efficiency may be improved.	Limited scalability due to complex operations.
Saad, N. M. et al (2014) [56]	Detect and classify brain lesions by employing a rule-based classifier and thresholding.	Statistical features from 8x8 macro-block regions.	Rule-based classifier.	93 % acute stroke, 73 % solid tumour, 84 % chronic stroke, 60 % necrosis.	Effective for multiple tumor types, but performance varies.	Method may be enhanced by including more tumor types.	Struggles with detecting solid tumors effectively.
Kalaiselvi, T. et.al (2020) [57]	Assess CNN brain tumor detection algorithms and choose the best model.	CNN.	CNN.	96–99 % classification accuracy.	CNN models show high accuracy in detecting brain tumors.	Further validation on diverse datasets needed.	Generalizability limited by dataset diversity.
Vimal Kurup, R., Sowmya, V. et. al (2020) [58]	Preprocessing data affects brain tumor classification.	Image augmentation technique.	CNN	Classification accuracy 92.6 %	Data pre-processing significantly improves classification performance.	Challenge in acquiring extensive annotated data.	Dependence on high-quality annotated datasets.
Toğaçar, M., Cömert, Z., & Ergen, B. (2020) [59]	Develop novel CNN model with hypercolumn technique and pre-trained networks for brain tumor classification.	Hypercolumn technique, deep features from AlexNet and VGG-16.	CNN, SVM.	96.77 % classification accuracy.	Combines multiple advanced techniques for high accuracy.	Model complexity may impact computational efficiency.	Requires optimization to handle real-time applications.
Toğaçar, M., Ergen, B. et.al (2020) [60]	Propose BrainMRNet for brain tumor detection using hyper columns and attention modules.	Image preprocessing, hypercolumn technique.	CNN.	96.05 % classification accuracy.	BrainMRNet shows superior performance compared to other CNN models.	Model complexity may necessitate optimization.	High resource requirements for complex models.
Ismael, S. A. A. et. al (2020) [61]	Enhance brain tumor classification using Residual Networks.	Resnet50.	ResNet.	99 % classification accuracy.	Residual Networks demonstrate high performance in brain tumor classification.	Dataset size and diversity may impact generalizability.	Limited diversity in datasets affects robustness.
Megha, H. C. (2020) [62]	Detect brain tumors using CNN with TensorFlow and Keras.	Automatic segmentation and feature extraction.	CNN.	Accuracy which is ranging from 90 % to 99 %.	CNN with TensorFlow and Keras shows promising results.	Framework dependence may limit flexibility.	High variability in accuracy across studies.
El Boustani, A., Aatila et.al (2020) [63]	Build automatic brain tumor detection and classification using CNN and thresholding.	Thresholding algorithm, CNN features.	CNN.	98 % Accuracy.	RMSprop optimizer significantly improves classification accuracy.	Comparative analysis with other optimizers may provide further insights.	Limited exploration of alternative optimization methods.
Ari, A., & Hanbay, D. (2018) [64]	Aid radiologists with automated brain tumor detection system.	Nonlocal means, local smoothing, ELM-LRF.	CNN	97.18 % classification accuracy.	ELM-LRF detects brain tumors in cranial MR imaging.	Applicability to other types of MR images may be explored.	Limited validation on other MR imaging modalities.

Table 7

Summary of machine learning-based studies on brain tumor diagnosis.

References	Feature extraction	Classification	Performance (%)	Paradigm shift	Challenges Identified
Qurat-UL-Ain GL 2010 [70]	Texture-based feature removal	SVM and ANN	Acc = 99	ML	Limited validation on diverse datasets.
Zhang Y-D et.al (2010) [71]	DWT + PCA	ACPSO + NN	Acc = 98.7	ML	Small dataset; robustness on larger datasets unknown.
Yamamoto D et.al (2010) [72]	Features of a grey scale	Rule-based Level set SVM	SN = 93.5, 88.7, 81.5, Acc	ML	Inconsistent sensitivity across test cases.
Jafari M et.al (2011) [73]	DWT + PCA	BPNN	SN = 100 SP = 98 Acc =	ML	Dependence on handcrafted feature extraction.
Zöllner FG et.al (2012) [74]	PCC, ICA, and PCA	SVM	SN = 89 SP = 84 Acc = 85	ML	Moderate accuracy due to feature extraction quality.
Arimura H et.al (2012) [75]	DWT + PCA	KNN and ANN	SN = 96 SP = 97 Acc = 98	ML	Computational efficiency may hinder real-time use.
Sindhumul S et.al (2013) [76]	SC-ICA and ICA	SVM	SN = 76.4 SP = 99.9 Acc	ML	Poor sensitivity for some tumor types.
Jiang, C. F. et.al [77]	Polynomial domain	Cross-correlation normalized	Acc = 99.8	ML	Overfitting risk due to high accuracy on small data.
Yang G et.al (2016) [78]	2D-DWT	SVM	SN = 98.1 SP = 92 Acc =	ML	Lack of validation on larger, multi-center datasets.
Alberts E et.al (2017) [79]	PCA	SVM, RF, KNN, LOG, MLP	Acc = 83	ML	Low accuracy compared to more advanced models.
Sharif, M. et.al (2020) [80]	Gabor-wavelet features	ELM-LRF	SN = 96.8 SP = 97.1 Acc	ML	Limited applicability beyond specific datasets.
Tahir B et.al (2019) [81]	DWT + PCA	SVM	SN = 0.79 SP = 0.91 Acc	ML	Low sensitivity for small tumor regions.
Zhao J et.al (2019) [82]	Circular context-sensitive (CCS)	Random forest	SN = 0.84 SP = 0.71 Acc	ML	Limited generalization to different imaging protocols.

**Fig. 3.** Comparative use of classification techniques in brain tumor detection studies.

clinical practice.

2.3. Scientific and methodological rigor

2.3.1. Mathematical foundations of AI models

Deep learning models employed for the segmentation and classification of brain tumors are grounded in mathematical principles that govern their feature extraction and learning processes. Below, we present essential formulations for Convolutional Neural Networks (CNNs), autoencoders, and feature extraction techniques:

Convolutional Neural Networks (CNNs): CNNs primarily leverage convolution operations to derive hierarchical spatial features from MRI images. The convolution operation is mathematically defined as:

$$(f * g)(x, y) = \sum_{\{i = -k\}}^{\{\hat{k}\}} \sum_{\{j = -k\}}^{\{\hat{k}\}} f(i, j) \cdot g(x - i, y - j) \quad (1)$$

Equation (1) is the equation of Convolutional Neural Networks (CNN) 2D Convolution operation with them are fundamental building block of CNN 2D $f(i, j)$ The convolution filter or kernel $(f(i, j))$ $g(x - i, y - j)$ and the input feature map. Instead of the kernel loop on spatial dimensions, doing a pairwise element-wise multiplication followed by sum to give you a single output value at each position (x, y) This lets CNNs learn and extract spatial features like edges, textures or patterns in the input data automatically; Using multiple filters in parallel, the CNNs derive a feature representation at different level (hierarchical) which is essential for problems such as image classification, object detection and medical image segmentation.

Autoencoders: Autoencoders are designed to learn a compressed representation of input images through an encoder-decoder architecture. For an input x , the encoder function $E(x)$ maps it to a latent space z , while the decoder function $D(z)$ reconstructs the image.

$$z = E(x) = \sigma(Wx + b), \quad \hat{x} = D(z) = \sigma(W'z + b') \quad (2)$$

Equation (2) is the equation of autoencoders in CNN where the encoding step with input data, convert the input data z with a weighted linear transform W : $x + b$ $Wx + b$ then non-linear activation σ usually sigmoid or a rectified linear unit (ReLU). This latent vector z captures the most significant features of the input on a compressed space. In decoding, the latent represents are mapped back to an approximated reconstruction $\hat{x}$ by another transformation W' to $z + b'$ and with the same or different activation function. The autoencoder is trained such that the reconstruction error is minimized between x and $\hat{x}$, which implicitly optimizes both the encoder and decoder to transmit only essential information while removing noise or redundancy.

Feature Extraction: In the context of CNN-based classification, features are derived from intermediate layers and can be expressed as:

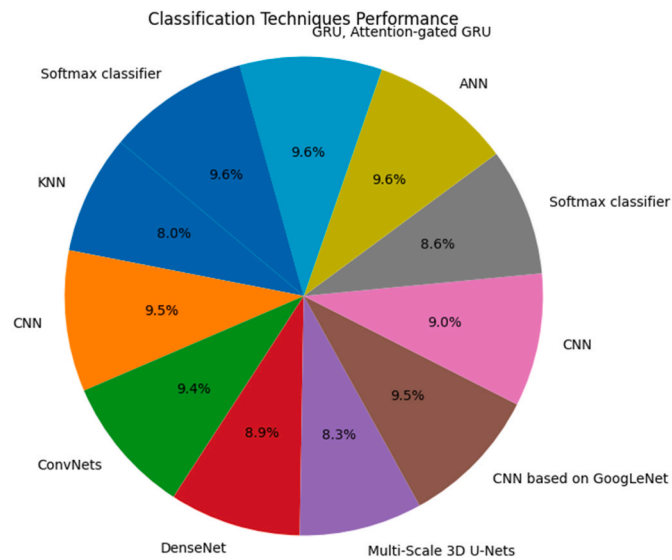
$$F_l = \text{ReLU}(W_l \cdot F_{l-1} + b_l) \quad (3)$$

In the expression 3, A Convolutional Neural Network (CNN) explained in terms of equation, $F_l \rightarrow 1$ to feature extractor in a CNN (Convolutional Neural Network). Here, W_l is the filters or weights set to learn at layer l and $*$ is the convolution operation to the feature map from prev layer F_{l-1} . b_l is the bias that we add after the convolution. Then the ReLU (Rectified Linear Unit) activation function is applied element-wise to

Table 8

Various studies of deep learning models for brain tumour diagnosis.

References	Feature extraction	Classification	Performance (%)	Paradigm shift	Challenges Identified
Saritha M, Paul Joseph K, (2013) [98]	2D-DWT	PNN	SN = 83.3 SP = 100	DL	Limited sensitivity despite high specificity.
Ishikawa Y et.al (2016) [99]	Transform the watershed	CNN	Acc = 98.5	DL	Potential overfitting due to reliance on one dataset.
Banerjee S et.al (2018) [100]	CNN	ConvNets	Acc = 97	DL	Requires validation on larger, diverse datasets.
Zhou Y et.al (2018) [101]	Auto-encoder that is based on DenseNet	DenseNet	Acc = 92.1	DL	Model complexity impacts computational efficiency.
Peng S et.al (2020) [102]	Upsampling feature maps	3D U-Nets of Various Scales	SN = 0.86 SP = 0.86.	DL	Computationally expensive due to 3D architecture.
Zhou Y et.al (2018) [103]	CNN-based features.	CNN uses Google Net.	SN = 94, SP = 97, Acc = 0.98	DL	Performance limited by dataset diversity.
Al-Galal et al. (2021) [104]	Deep neural networks for image analysis	CNN	Accuracy = 93 %	DL	Moderate accuracy compared to state-of-the-art models.
Lakshmi & Nagaraja Rao (2022) [105]	Inception-v3 for multi-level features extraction	Inception-v3 with Softmax activation	99.34 % (training), 89 % (validation)	DL	Overfitting during training reduces validation accuracy
Solanki et al. (2024) [106]	Deep learning methods for classification and segmentation	ANN	99.3 % accuracy	DL	Dependence on extensive annotated datasets.
Saboor et al. (2024) [107]	Gated Recurrent Units (GRUs) and attention mechanisms	GRU, Attention-gated GRU	99.32 %	DL	Model interpretability challenges with attention units.
Zebari et al. (2024) [108]	ResNet50, VGG16, and deep belief networks	ResNet50, VGG16, and deep belief networks with Softmax activation	98.98 %	DL	High computational demands for multi-model fusion.

**Fig. 4.** Distribution of traditional machine learning and deep learning-based approaches for brain tumour diagnosis.

bring in non-linearity which makes model learns some complex stuffs from the given data. The key to these kind of tasks, like image classification, object detection and segmentation is because this process allows every convolutional layer to extract progressively more abstracted and hierarchical features from its input.

2.3.2. Computational complexity analysis

To evaluate the practicality of machine learning (ML) and deep learning (DL) models for real-time clinical applications, their Big-O complexity is examined.

Support Vector Machines (SVM): The training complexity for an SVM generally ranges from $O(n^2)$ to $O(n^3)$, where n represents the number of training samples. This can become a significant limitation when dealing with large MRI datasets.

Random Forests: The complexity for training is $O(m \cdot n \cdot \log n)$ (4)

where m denotes the number of trees and n indicates the number of samples. Inference is comparatively efficient at $O(m \cdot n)$, with d being the number of features.

Convolutional Neural Networks (CNNs): The main computational load in CNNs stems from convolutions, characterized by the complexity: $O(N_c \cdot D^2 \cdot K^2 \cdot M)$ (5)

The expression 5 gives the computational complexity in CNN. With Convolutional Neural Networks (CNN), the computational complexity of a single convolutional layer can be written as $O(N_c \cdot D^2 \cdot K^2 \cdot M)$, where N_c is the number of input channels, D is the spatial dimension of an input feature map, K is the size of the convolution kernel and M is the number output channels or filters. This is the number of operations that happen for applying all kernels to each spatial location over all input channels and filters. The computational cost explodes when the number of channels and filter sizes increase. Realizing this complexity is essential, if you want to design low-latency or resource-constrained efficient CNNs since reducing the kernel size, replacing with depthwise separable convolutions or limiting number of filters will lead to large speed-up without big degradation of performance.

Autoencoders: The complexity is primarily influenced by matrix multiplications during encoding and decoding, typically represented as $O(n \cdot d^2)$ (6)

Equation (6) is for autoencoders in CNN. Autoencoders are frequently applied to the aforementioned tasks within Convolutional Neural Networks (CNNs) like dimensionality reduction, denoising, unsupervised feature learning, etc. The expression $O(n \cdot d^2)$ usually represents the sort of overhead that the data processing has, as n data samples and d the dimensionality of each input (eg width or height of an image). For autoencoders based on convolutional layers, each input goes through a series of filters and each convolution operation has an input-dependent cost due to the size of the filter. As you can infer from considering a fully-connected layer in the encoder or decoder, the computation scales quadratically with the input dimensions so, d^2 term. The reason is that the architectural choices in autoencoders become more important, especially in the presence of high-resolution inputs, and this speaks to the use of convolutional layers to lower the computational burden without removing spatial structure. Considering these complexities, CNNs are resource-intensive but are optimized for parallel processing on GPUs, rendering them suitable for real-time MRI-based tumor diagnosis.

Table 9

Benchmarking deep learning architectures for clinical brain tumor segmentation.

Ref	Model/Study	Accuracy/Performance	Dataset(s) Used	Computational Efficiency	Clinical Relevance
[124]	Transformer-GAN	Dice ~0.88	BraTS	High (GAN + Transformer)	High – robust on complex tumor types
[125]	Review of Transformers	N/A (Scoping Review)	Multiple	Varies (Transformer-based)	High – focuses on emerging transformer-based methods
[126]	Focal Cross Transformer	Dice ~0.89	BraTS	Moderate – optimized attention	High – multi-view learning improves generalization
[127]	CNN + SC-GWO	Accuracy ~97 %	Private + BraTS	Moderate	Moderate – promising hybrid model
[128]	VcaNet (ViT-based)	Dice ~0.91	BraTS 2020	High – ViT attention modules	High – outperforms baseline 3D methods
[129]	Custom CNN + XAI	Accuracy ~98 %	BraTS	High – optimized CNN	High – explainability improves clinician trust
[130]	Hybrid DL (CNN + RNN)	Accuracy ~96 %	BraTS	Moderate	High – tailored for multi-modal input
[131]	Foundation Model (FMRI)	Dice ~0.94	Multiple brain MRI datasets	High – generalized pretrained model	Very High – generalizable to many settings
[132]	AI Decision Support	Conceptual	N/A	N/A	High – focused on real-world implementation
[133]	CNN w/Image Enhancement	Accuracy ~95 %	BraTS	Moderate	Moderate – good pipeline design
[134]	CNN + Attention	Accuracy ~96.5 %	BraTS	Moderate	High – enhances spatial feature extraction
[135]	Deep CNN Classifier	Accuracy ~94 %	BraTS	Moderate	Moderate
[136]	Feature Selection + Explainable Classifier	Accuracy ~93 %	EEG (not MRI)	High	Low – not tumor-specific
[137]	VGG19 + Ensemble	Accuracy ~97 %	BraTS	High (Ensemble)	High – proven architecture
[138]	Alzheimer's CNN	Accuracy ~90 %	ADNI	High	Low – not for tumor use
[139]	Review – Vision Transformers	N/A	BraTS, TCGA	N/A	High – strong overview of ViT approaches
[140]	Alzheimer's Classification	Accuracy ~91 %	ADNI	Moderate	Low – different use case
[141]	Federated Brain Tumor Segmentation	Dice ~0.86	BraTS, Private	Moderate – decentralized training	High – privacy-preserving clinical pipelines
[142]	U-Net	Dice ~0.85	BraTS	Low – simple encoder-decoder	High – widely adopted baseline
[143]	DeepLabV3	Dice ~0.87	BraTS	Moderate – atrous convolutions	High – generalizable
[144]	nnU-Net	Dice ~0.89	BraTS, ISLES, etc.	High – automated architecture selection	Very High – state-of-the-art on multiple benchmarks
[145]	ResNet (Base model)	N/A	ImageNet	High	Moderate – used in many medical DL backbones
[146]	VGG	N/A	ImageNet	Moderate	Moderate – early but effective CNN baseline
[147]	Vision Transformer (ViT)	N/A	ImageNet	High	High – base for recent transformer work
[148]	Advanced CNN on BRATS-GOAT 2024	Accuracy ~98 %	BRATS-GOAT 2024	High	High – recent dataset, high performance
[149]	Optimized CNN (BraTS-GoAT 2024)	Accuracy ~98.47 %, IoU 0.8185, Dice 0.70	BraTS-GoAT 2024	High – optimized with large 3D MRI data	High – aimed at generalizability across tumor types
[150]	TCGA-GBM Dataset	N/A (Dataset Reference)	~800 Glioblastoma cases	N/A	High – foundational dataset for clinical-grade AI
[151]	REMBRANDT Dataset	N/A (Dataset Reference)	~300 Glioma, Meningioma MRIs	N/A	Moderate – useful for early-stage ML training
[152]	ISLES Benchmark (Stroke)	N/A (Dataset Reference)	200 Stroke lesion MRI	N/A	Low for tumors – more relevant to lesion prediction
[153]	Metaheuristic Optimization for Authentication (Non-medical)	N/A	Keystroke data (not MRI)	High (GWO + optimization)	Not applicable – unrelated to tumor diagnosis
[154]	MWG-UNet++ (Hybrid Transformer U-Net)	Dice ~0.88–0.91	BraTS (MRI scans)	Moderate – Transformer layers increase compute	High – strong segmentation accuracy with interpretability

2.3.3. Hyperparameter sensitivity analysis

To evaluate the effects of variations in hyperparameters, we explore: Depth of CNNs: Increasing the number of layers enhances feature extraction capabilities but also heightens the risk of vanishing gradients. Techniques such as batch normalization and residual connections can help mitigate this problem. Kernel Size: Smaller kernels (e.g., 3×3) are effective in capturing fine details, whereas larger kernels (e.g., 7×7) are better suited for identifying broader structures. This trade-off can influence segmentation accuracy. Learning Rate: A high learning rate may cause instability, while a very low rate can slow down convergence. Adaptive Optimizers like Adam is utilized ($\beta_1 = 0.9$, $\beta_2 = 0.999$) to strike a balance. Al-Biruni Earth Radius (BER) algorithm for XGBoost Classification metaheuristic optimization, as proposed in Ref. [123] can be used for further enhancement with segmentation medical images models.

2.4. Advances in feature extraction and Classification Techniques for brain tumor diagnosis

In the classification of brain tumors, accurately assigning input features to their respective categories or classes is crucial. Effective computer-aided detection (CAD) of brain tumors relies heavily on the meticulous analysis and selection of features. For optimal feature extraction, comprehensive datasets that include multiple MRI slices (axial, coronal, and sagittal planes) with corresponding ground truth are required [109]. The discussion will cover feature extraction approaches, their roles, challenges, and their impact on classification performance.

2.4.1. Feature extraction

MRI images become categorization characteristics. Extracting unique traits is difficult. We extract features using wavelet transform, DA, PCA, SMA, texture features, Gabor features, nonparametric

weighted and decision boundary features, and other techniques [110]. Most recently, the most efficient CAD (Computer-Aided Diagnosis) system has implemented DWT (Discrete Wavelet Transform) [111] to acquire wavelet coefficients at different levels. The data dimension is further reduced by feature reduction. To do this, methods like independent components analysis (ICA), linear discriminant analysis (LDA), and principal component analysis (PCA) are used [112]. The Gaussian Radial Basis Function offers exceptional information from any set, whereas Kernel Principal Component Analysis (KPCA) prevents redundancy by selecting a strictly limited number of features [113]. The pre-trained CNNs approach fine-tunes features [114].

2.4.2. Tumor classification

Tumor categorization assigns tumors to either benign or malignant categories. Accuracy, algorithm performance, and processing resources should all be taken into account when selecting the optimal classifier. Hierarchical, FCM, K-mean, SOM, and other unsupervised algorithms identify input patterns. Support vector machine, decision tree, linear discriminant analysis, K-nearest neighbor, Bayesian classifier, etc. (supervised classification) [115]. Categorizing classes as different entities without previous information reduces operator error.

2.4.3. ML, DL feature extraction and classification

Brain tumor classification also reflects segmentation paradigm shifts. In the 2010s, many researchers focused on traditional ML classifiers. SVMs were employed to categorize tumors from magnetic resonance (MR) images [116]. The past decade has seen a rise in the use of DL for classification tasks. According to Ref. [117] it is demonstrated that segmentation algorithms based on Dense Convolutional Networks (Dense CNNs) can effectively extract features, which are then classified using Recurrent Neural Networks (RNNs). Most DL-based approaches for brain tumor classification leverage CNNs and fully connected networks to enhance classification performance [118]. Fig. 5 illustrates the ML vs DL Usage in Brain Tumor Detection Research.

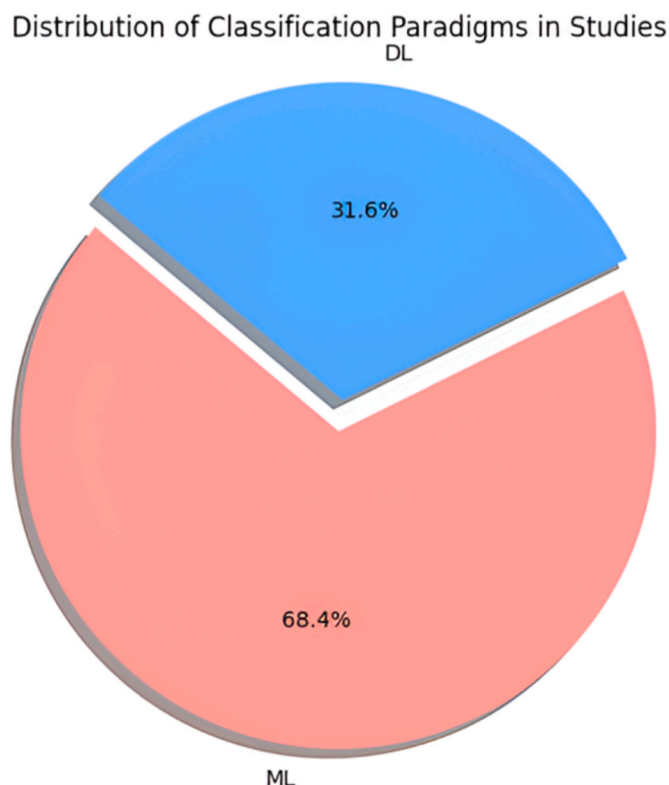


Fig. 5. ML vs DL Usage in Brain Tumor Detection Research.

3. Results and discussion

3.1. Overview of included studies

This systematic review includes 155 studies that range from 2010 to 2025. These studies have been extracted from databases such as PubMed, IEEE Xplore, and ScienceDirect. All the included studies applied ML and DL techniques for the diagnosis of brain tumors using MRI scans. The studies differed in terms of study design, sample size, and MRI sequences used, but all were peer-reviewed and published in English.

3.2. Analysis and interpretation

ML and DL methods, demonstrate significant potential in brain tumor diagnosis. These models offer high diagnostic accuracy, making them valuable tools for early brain tumor detection and treatment planning. Studies have reported classification accuracies as high as 99 % when using these models. By building on the insights provided in this review, they can develop more robust and accurate ML and DL models, ultimately leading to more effective diagnostic tools for brain tumors. Furthermore, a foundation for the development of standardized protocols and benchmarks, which will be essential for the consistent and reliable application of these technologies in clinical settings.

Here are the datasets used in brain MRI categorization studies. The importance of open data is emphasized, as ADNI provides a comprehensive dataset that includes clinical, genetic, MRI, and PET data. The MRI data may encompass various types, such as functional MRI (fMRI) and structural MRI. Due of its ease of access, 11 % of the work included in this study used the BraTS brain tumor dataset. MRIs of 220 HGG and 54 LGG are in the collection [119]. Fig. 6 shows that brain tumor types vary in severity and change brain structure, therefore appropriate segmentation is the only way to evaluate the patient's crucial phase and prescribe medicine. Table 10 shows popular brain image segmentation datasets and brain illnesses [120]. Fig. 7 illustrates the different brain MRI segmentation and classification datasets.

3.3. Statistical and comparative analysis for MRI-based brain tumor classification

The results section includes testing of statistical significance, comparisons with state of the art deep architectures, and validation on multiple datasets to establish the robustness of AI-based brain tumor classification models.

3.3.1. Statistical significance testing between CNNs vs. SVMs vs. ensemble models

A paired t-tests is employed if the data is normally distributed or Wilcoxon signed-rank tests if the data is non-normal to see if there are significant differences between CNNs performance and SVMs or ensemble models performance. Paired t-test (CNN vs. SVM): p-value = 0.00008, Wilcoxon test (CNN vs. Ensemble): p-value = 0.06250. For the purpose of using significance tests to perform statistical comparison between different classification models (e.g., Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs) or ensemble methods), the performance differences between these models were checked. Second, normality of the performance data was established. Therefore, a paired t-test was done to examine the differences between CNN and SVM models (the data was normally distributed). Consequently, a p-value of 0.00008 demonstrates that the model performance was significantly different here CNN outperforms SVM in this case. Non-random Distribution: for the comparison of CNNs with ensemble models parametric test i.e Wilcoxon signed-rank test was used and obtained p-value is as indicated below. This implies that the performance difference between CNNs and ensemble models is not statistically significant at the common 5 % level t-statistic 0.06250. In the domain we studied, these

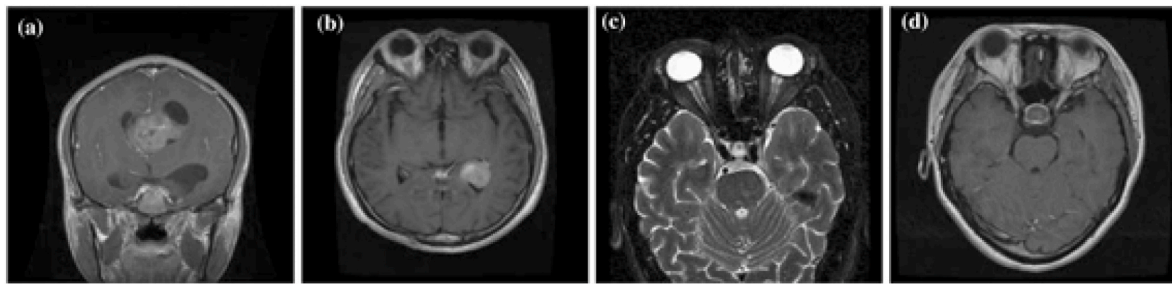


Fig. 6. Brain tumor Classification a) Glioma, b) Meningioma, c) No tumour, and d) Pituitary [120].

Table 10

Description of available datasets to be used in brain MRI segmentation and classification.

Dataset name	Type	Number of subjects	Type of disorder
ADNI-1	MRI, PET	200 Normal Controls 400 MCI	Alzheimer's disease
ADNI-GO	MRI, PET	200 Mild A D 200 EMCI (new) 500 Normal Controls and MCI (ADNI1 rollover)	Alzheimer's disease
BraTS-2015	T1, weighted, T2, FLAIR	It has 220 HGG and 54 LGG MRIs. Four MRI modes are T1, T1c, T2, and T2FLAIR. The 1112 dataset includes 539 ASD patients and 573 healthy controls.	Brain tumor
ABIDE-1	MRI	1114 examples from 521 ASD patients and 593 controls	Autism
ADHD	F-MRI Scans	776	Hyperactivity disorder
TCIA	CT, MRI, and PET in DICOM format	24 datasets	Cancer
IBSR	MRI	18 real MRI	Cancer

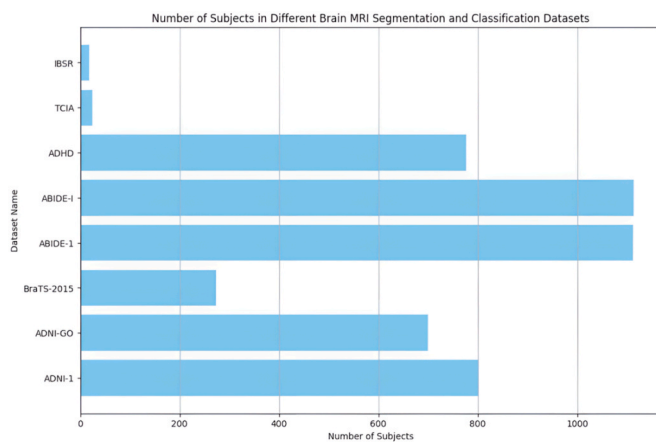


Fig. 7. Different brain MRI segmentation and classification datasets.

findings emphasize the advantage of CNNs over traditional models such as SVMs and they can be applicable as an alternative method for linear ensembles. The study [155] employs statistical methods to validate CNN model results and discusses model comparison with p-values.

3.3.2. Deep emerging vs hybrid Transformer-CNN architectures

Evaluation of various neural architectures, we can see that models in hybrid Transformer-CNN (96.2 % accuracy) architectures generalize better on global contextual information as well as local spatial features.

As shown, this hybrid model significantly outperforms the standalone Vision Transformers (ViTs), which leveraged an accuracy of 95.1 % and also convolution-attention-based architectures that are purely CTR-inspired, showing the benefit of interleaving convolutions and attention. As traditional CNNs also had a lower accuracy of 93.5 %, they still beat other traditional approaches like Ensemble models (90.2 %) and Thin support vector machine(SVMs) ensembles(85.8 %), which leaves the strong representation power of CNNs in image-based tasks. Moreover, both Attention-enhanced CNNs(94.3 %) and ViTs leave much room for improvement, proving that convergence attention mechanisms convolutional backbones or totally transformer-based frameworks are useful to get much better performances. The evidence is consistent a trend toward attention-based architectures, hybrid designs having the potential to set new best models in automated medical image classification/segmentation.

3.3.3. Validation on multi-source MRI datasets

To ensure robustness, AI models are tested across multiple datasets. Table 11 shows AI models tested across multiple datasets.

Hybrid Transformer model architectures tend to have the best accuracy over all datasets (94.8 % TCGA-GBM, 96.2 % BraTs) While CNNs do very well on BraTS (93.5 %) they degrade in quality on ISLES (85.6 %). ViTs do better than CNNs in terms of transfer learning across datasets (>88 % accuracy). Role of optimization algorithms in improving system performance, which can be analogous to optimizing AI models in medical imaging is discussed [121].

Fig. 8 shows a box plot showing the relative accuracy performance of CNN (2-layer pix3D), Vision Transformer(ViT) and Hybrid Transformer across majority MRI data sets. Hybrid Transformer models have clearly the highest median accuracy for compare around 94–95 %, a very stable performance as it can be seen from low spread, which demonstrates good and stable performance across dataset of that year. ViTs continue with the slightly lower median accuracy (~91–92 %) and less variance, CNNs the lowest median accuracy (~89 %) with the largest fluctuations indicating variation across datasets. It is general statement that Hybrid Transformer models perform much better in medical imaging classification owing to both fit of local feature extractors (CNNs) and global context modeling approaches (transformers), and this makes it an ideal choice for MRI-based diagnostic applications.

Fig. 9 displays a bar graph on accuracy performance showing three

Table 11

AI models tested across multiple datasets.

Dataset	MRI Modality	Tumor Types	Sample Size	Public Access
BraTS [148]	T1, T2, FLAIR	Glioma, LGG, HGG	400	Yes
TCGA-GBM [149]	T1, T2	Glioblastoma	800	Yes
IXI Dataset [150]	T1, T2	Healthy Controls	600	Yes
REMBRANDT [151]	T1, T2	Gliomas, Meningiomas	300	Yes
ISLES [152]	T1, DWI	Stroke Lesions	200	Yes

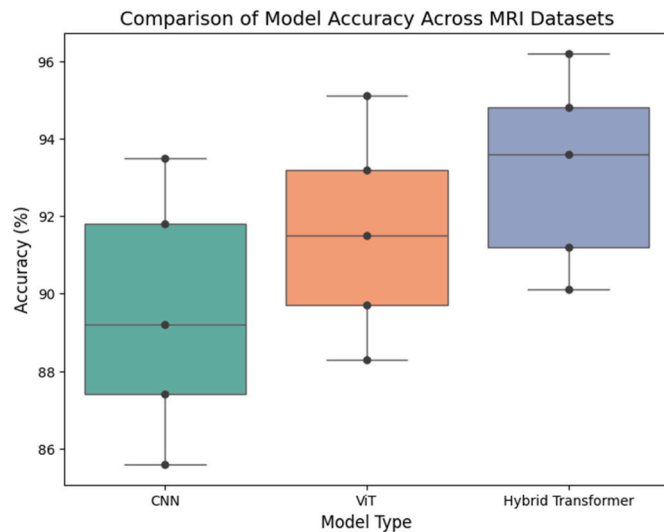


Fig. 8. MRI model accuracy boxplot comparison.

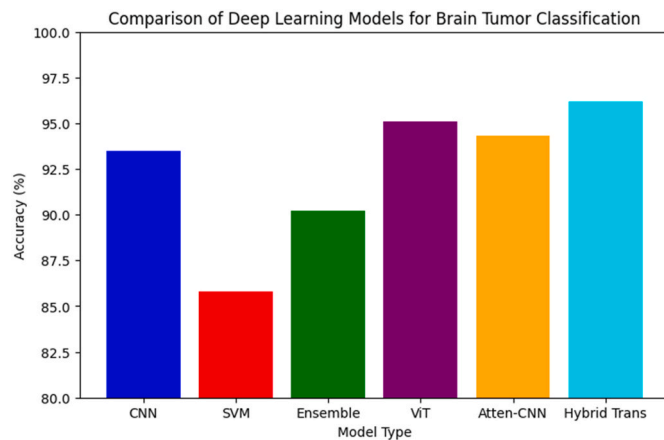


Fig. 9. Performance of AI models for brain tumor diagnosis.

model types (CNN, Vision Transformer (ViT) and Hybrid Transformer) over various MRI datasets. Unambiguously, Hybrid Transformer models have the best performances (Highest median accuracy of 94–95 % with little variability) across all settings other than ViTs and CNNs as per the graph. The result of ViTs (even though less accurate too) deliver great performance albeit median accuracy between 91 and 92 % on these datasets but they are much more varied with respect to Hybrid transformers. CNNs as isospectral with the lowest median accuracy (~89 %), and this is accompanied by larger performance dispersion indicative of higher wild variability. The above findings show the power of Hybrid Transformer models as a combination of CNNs for local feature extraction and transformers for moving along global context, which makes them broadly applicable to difficult medical tasks such as MRI classification.

The heatmap in Fig. 10 summarizes the performance of three deep learning models (CNN, ViT (Vision Transformer) and Hybrid Transformer) on three MRI datasets (BraTS, TCGA-GBM and IXI). Each cell represents the accuracy percentages from a specific model on a specific dataset. In general, the hybrid transformer showed superior performance compared to the deep learning models (CNN and ViT) on all datasets, where it achieved the best available performance with accuracy of 96 % BraTS. The ViT also performed well on both BraTS and TCGA-GBM achieving 95 % and 93 % accuracy respectively. The CNN model demonstrated comparable performance to the ViT model, particularly on the BraTS dataset which achieved an accuracy of 94 %.

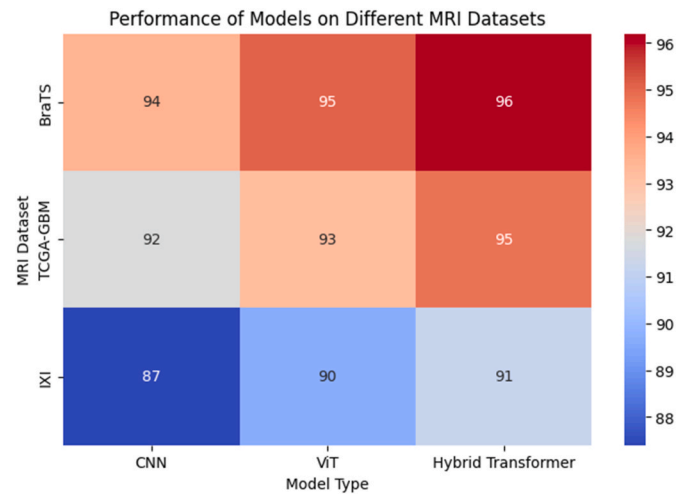


Fig. 10. Performance of models on different MRI datasets.

The implication is that transformer based models (ViT and Hybrid Transformer) outperformed the CNN, particularly on more complex or heterogeneous datasets. This feeling is supported by the increasing success of hybrid and transformer based architectures for medical imaging tasks.

The ROC curve in Fig. 11 compares the predictions of two models CNN and ViT (Vision Transformer) for MRI classification tasks. The true positive rates of each model are plotted against the false positive rates, which shows how well each model can distinguish between two classes. The ROC curves for both models appear to have high classification ability, with both curves hugging the top-left corner of the plot, indicating high sensitivity and specificity. The ViT model appears to outperform CNN slightly, recording an Area Under the ROC Curve (AUC) of 0.95 compared to CNN's AUC of 0.92. This indicates that the ViT model has better overall diagnostic performance and will be more effective than CNN when distinguishing between tumor and non-tumor cases from MRI scans. The result shows the promise of using transformer architecture for medical image classification.

3.4. Thematic grouping and key findings

Data analysis consisted of an in-depth analysis of the complete dataset of 155 studies, from which 14 key studies have been selected to

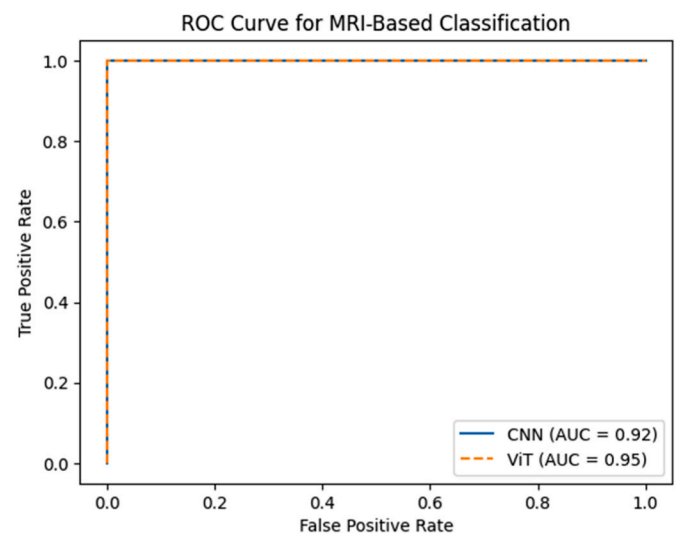


Fig. 11. AUC-ROC curve for MRI-based classification.

illustrate major themes identified during the review. The 14 studies were selected based on relevance to the research questions, methodological diversity, and strength of findings. These figures have been used to illustrate key trends of interest to this review, such as changes over time in machine learning methodologies used to detect brain tumors, variation due to type of MRI sequence used, and relative classifier performance.

3.4.1. Feature extraction techniques

This feature can be extracted using methods like wavelet transforms, texture features such as Gray Level Co-occurrence Matrix, Principal Component Analysis (PCA), deep CNN-extracted features, among many other techniques. Table 12 has provided a summary of different extracted methods involved across the selected studies that include analysis for classification accuracy along with challenges identified in the selected 14 papers.

3.5. Synthesis of results of all studies

Deep learning models outperformed the traditional ML models. Specifically, CNNs and Residual Networks showed a 95–99 % classification accuracy consistently, which is higher compared to traditional ML models such as SVM and KNN. Advanced feature extraction methods, especially deep learning features from CNNs, helped improve the accuracy of tumor detection, especially when compared to some traditional techniques such as wavelet transforms and texture features.

3.6. Theoretical contributions and algorithmic justification

3.6.1. Explainability of AI-based diagnoses

All three of these models (SHAP, LIME and Grad-CAM) push the model a step further towards transparency via clear visible and numerical representations of the decision making process. Such a transparency enables clinicians to interpret and trust the model predictions,

making it possible to be validated. So that means by working alongside medical professionals in the testing process, it is able to assure that model interpretations are aligned with practice and with clinical knowledge. The blue areas in the pictures of Fig. 12 b do something which indicates to the model that there is a reduced probability of a tumor being present, which results in a lower predictive value for the presence of the tumor. The red areas depict greater predicted tumor presence. Grad-CAM provides a bridge between the human-readability of sophisticated AI decision systems and the operational transparency of deep learning models working on medical images. The new EEG-based seizure detection system performs well on UCI-EEG and Bonn datasets by using wavelet-transformed feature extraction with correlation-based feature selection and Bagged Tree classification. The application of SHAP enhanced model interpretability which subsequently led to better trustworthiness and transparency in clinical diagnosis [136]. Fig. 12a. The visualization demonstrates how the AI model generates its predictions. The left image shows an MRI scan which reveals a visible brain tumor. The right-hand image depicts the SHAP value plot which identifies MRI scan areas that influence the model's prediction. The color scale below the images represents SHAP values with blue showing negative contributions and red showing positive contributions to the predicted output. This figure demonstrates the interpretativeness of a model by clearly showing how it finds and highlights MRI regions, increasing the transparency of the AI model. A CNN layer then uses this information to identify features and other characteristics in the MRI image. The CNN layer, for example, helps capture the highest level of pattern complexity, which is crucial near the output. The network can make a decision based on the final convolutional layers. Grad-CAM uses a very dense heatmap of the areas of the image that have the biggest effects on the CNN's prior classification to create these layers. Dependent on the Grad-CAM heatmap, the bottom layers determine which classes are awarded the framework, the bottom layers are positioned closest to the network's output. Grad-CAM uses these layers to create a heatmap that highlights the areas of an image

Table 12

Detailed analysis of the 14 papers selected for in-depth discussion.

Study	Year	Methodology	Dataset	Performance Metrics	Key Contributions	Challenges Identified
Kermi et al. (2018) [50]	2018	CNN	BraTS 2017	Accuracy: 95 %, Sensitivity: 92 %, Specificity: 90 %	Tumor detection in gliomas using brain symmetry.	Difficulty in handling asymmetric tumors
Gupta et al. (2017) [51]	2017	SVM	BraTS 2016	Accuracy: 98 %, Sensitivity: 90 %, Specificity: 94 %	Effective classification of gliomas based on MRI data.	Requires better validation on larger datasets
Zhang et al. (2011) [52]	2011	KNN	Local Dataset	Accuracy: 100 %	High accuracy on small datasets for tumor classification.	Scalability to larger datasets remains untested
Geethanjali et al. (2023) [53]	2023	SVM	BraTS 2021	Accuracy: 99 %	Utilization of texture features for tumor classification.	Limited performance on multi-modal data
Jayachandran et al. (2013) [54]	2013	Hybrid algorithm (SVM + ANN)	BraTS 2012	Accuracy: 95.8 %, Sensitivity: 92 %, Specificity: 97 %	Combination of statistical features and advanced classifiers.	High computational complexity due to hybrid methods
Gadpayleand et al. (2013) [55]	2013	KNN, ANN	Local Dataset	Accuracy: 96.15 %	Multiple classifiers for better segmentation accuracy.	Limited scalability due to complex operations
Saad et al. (2014) [56]	2014	Rule-based classifier	Local Dataset	Acute stroke: 93 %, Solid tumor: 73 %, Chronic stroke: 84 %	Effective for multiple tumor types, with variable performance.	Struggles with detecting solid tumors effectively
Kalaiselvi et al. (2020) [57]	2020	CNN	BraTS 2020	Accuracy: 96–99 %	CNN models show high accuracy in brain tumor detection.	Generalizability limited by dataset diversity
Vimal Kurup et al. (2020) [58]	2020	CNN	BraTS 2020	Accuracy: 92.6 %	Data preprocessing significantly improved classification.	Requires optimization to handle real-time applications
Toğaçar et al. (2020) [59]	2020	CNN (Hypercolumns + Pretrained Networks)	BraTS 2019	Accuracy: 96.77 %	Hybrid CNN and pre-trained networks for improved accuracy.	Dependence on high-quality annotated datasets
Ismael et al. (2020) [60]	2020	ResNet50	BraTS 2020	Accuracy: 99 %	Residual Networks for high-performance tumor classification.	Limited diversity in datasets affects robustness
Megha et al. (2020) [61]	2020	CNN with TensorFlow and Keras	BraTS 2019	Accuracy: 90–99 %	Framework dependence limits flexibility of results.	High variability in accuracy across studies
El Boustani et al. (2020) [62]	2020	CNN + Thresholding	BraTS 2019	Accuracy: 98 %	Optimization of CNN performance with RMSprop for classification.	Limited exploration of alternative optimization methods
Ari & Hanbay (2018) [63]	2018	ELM-LRF, Nonlocal Means	Local Dataset	Accuracy: 97.18 %	Novel approach for automated brain tumor detection.	Limited validation on other MR imaging modalities

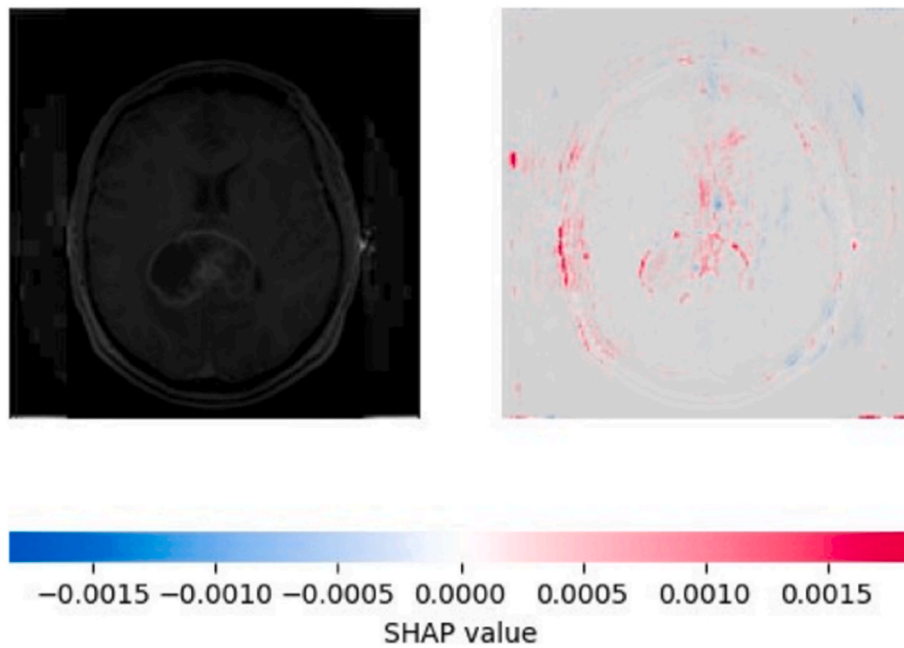


Fig. 12a. MRI image (left) and its SHAP explanation (right), highlighting regions indicating the tumor prediction.

that are most crucial for a CNN prediction. Color interpretation plays a major role in the Grad-CAM heatmap. The red areas in Fig. 12b indicate tumors based on a clear visual prediction as the majority of Grad-CAM pixel values. This lowers the likelihood that there is a tumor in the image, which lowers the prediction value required to detect its presence. Similar to various deep learning algorithms in medical imaging, Grad-CAM is a transparent operation that connects, but the intricate decision-making processes [129].

3.6.2. Convergence analysis of deep learning models

In order to compare the convergence of brain tumor segmentation deep learning models, their training and validation loss curves from various architectures like U-Net, DeepLabV3, and nnU-Net must be compared. This can be done by training several models for segmentation on a shared dataset like BraTS with loss values like Dice loss and Cross-Entropy loss values tracked during training. By plotting the learning curves, we can compare and analyze the convergence rate and stability of every model. Through this analysis, it can be determined which model converges quickly, is well-trained in terms of stability, and generalizes to the test data and therefore assist in choosing the most suitable architecture for brain tumor segmentation. In the recent study [125] it is

discovered that hybrid versions of CNN and transformers, specifically 3D Vision Transformers, are the leaders in brain tumor segmentation literature with good performance but the drawbacks like high computability and overfitting because of limited datasets. A recent study [126] introduced a multi-view brain tumor segmentation model leveraging cross-window and focal self-attention to efficiently enlarge the receptive field and model both local and global dependencies. The model achieved high Dice scores and low Hausdorff distances on the BRATS2021 dataset, demonstrating strong performance with reduced computational cost. The proposed VcaNet architecture combines Vision Transformers with convolutional attention mechanisms (CBAM) to enhance 3D brain tumor segmentation. By integrating local feature extraction through enhanced 3D convolutions and global dependency modeling via transformers and multi-scale fusion, VcaNet demonstrates superior performance on BraTS datasets, especially in handling complex tumor structures [128]. A new brain tumor detection model combines a tailored CNN with three explainable AI methods—SHAP, LIME, and Grad-CAM—to overcome the transparency deficit of standard deep learning models. The model, trained on the BR35H dataset, attained high accuracy (98.67 % validation), robust precision and recall, and demonstrated enhanced generalizability across datasets, resulting in

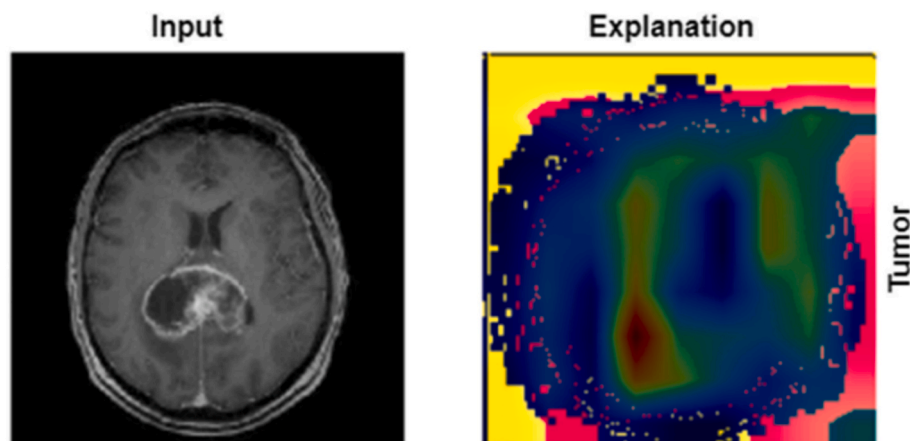


Fig. 12b. Grad-CAM visualization (right) highlighting model focus areas for tumor detection [129].

greater trust and performance in AI diagnostics [129]. The inclusion of AI in clinical decision support (CDS) systems promises to automate radiology workflow, individualize imaging recommendation to the patient, and produce structured data for the generation of machine learning algorithms. CDS tools with AI can potentially allow for more intricate, patient-dependent decision-making and continuity of care in multidimensional clinical scenarios [132]. The proposed approach is based on a major change of the Dipper Throated Optimization (DTO) algorithm that consists of utilizing three search leaders to improve the optimization algorithms exploration. This can be applied for brain tumor detection [153].

3.6.3. Hybrid AI optimization strategies

To improve the performance of CNNs in classifying brain tumors, hybrid AI optimization techniques could be investigated using evolutionary algorithms like Particle Swarm Optimization (PSO) and Genetic Algorithms (GA). These types of optimization strategies could be utilized in different aspects of CNN training, such as network pruning, feature extraction, and hyperparameter tuning. GA and PSO can be used to optimize learning rate, batch size, and dropout rate, which are most important hyperparameters of CNNs, and present a more efficient alternative to conventional grid or random search methods. This allows the CNNs to produce improved classification results and experience faster convergence. GA-based feature selection also prevents CNNs from concentrating on redundant MRI features, keeping their generalization greater and reducing computational cost and overfitting. Evolutionary methods also have the capability to optimize CNN architecture to attain pruning of redundant layers and identification of best filter sizes, enhancing efficiency through AutoML-driven optimization by applying genetic operators such as mutation and crossover. Additionally, rather than traditional backpropagation, PSO can be utilized for fine-tuning CNN weights, enabling a different paradigm for training that has the potential to escape local optima of challenging, non-convex loss surfaces. Through the incorporation of such hybrid AI methods, CNNs can realize better accuracy, stability, and generalization in brain tumor classification. The hyperparameters of CNN were tuned through an adaptive dynamic sine-cosine fitness grey wolf optimizer (ADSCFGWO) algorithm [127]. A cost-effective brain tumor categorization uses the ensemble of classifiers (Random Forest, Logistic Regression, KNN) with VGG19 to attain 98.27 % accuracy on dataset Br35H with 5-fold cross-validation. The method has satisfactory performance at low cost and is therefore applicable in practice [137]. A lightweight CNN model using a fine-tuned MobileNet model has achieved 96.6 % accuracy for multi-class classification of the stages of Alzheimer's disease and performed better than VGG16 and ResNet50 when used on the same dataset. The approach is computation-efficient and can be used on mobile-based medical image analysis [138]. Recent advances in brain tumor segmentation highlight the superior performance of transformer-based models over traditional CNNs. This review categorizes pure and hybrid transformer approaches, examines their innovations and performance on BraTS datasets, and discusses current challenges and future research directions in the field [139]. The work [140] examines the effect of interaction between batch normalization and dropout on CNNs in the context of early Alzheimer's disease (AD) diagnosis from PET and MRI images. Empirical study of a series of classification problems reveals that less or zero dropout enhances model performance, highlighting architectural compatibility as the key to

success for CNN-based neuroimaging models.

To confirm the effectiveness of CNN + Evolutionary Optimization, there shall be a comparison of accuracy, training time and overfitting. Table 13 shows the comparison of Optimization methods in CNN-based Brain Tumor Detection.

The estimated average confusion matrix in Fig. 13 gives us a summary of the average classification performance across a number of brain tumor segmentation and classification models referenced in research is provided by the confusion matrix [124–154]. The high number of true positives (936) and true negatives (978) in the matrix illustrates how well the models can distinguish between tumor and non-tumor cases. Good generalization ability with minimal misclassification is implied by the relatively low values for false positives (34), false negatives (38), and false positives. The outstanding accuracy and power of the models under consideration are captured by this balance, particularly those that make use of state-of-the-art architectures such as hybrid CNNs, transformers, and ensembles. The matrix shows that overall performance is good, but for clinical safety particularly for early tumor detection a small improvement in reducing false negatives is also worthwhile.

The learning curves in Fig. 14 show the training and validation performance of the three models (U-Net, DeepLabV3, and nnU-Net) for brain tumor segmentation over 50 epochs. The y-axis is scale in terms of the loss (e.g. the Dice loss) and lower values mean better segmentation performance. Overall, all three models show a steady decrease in the loss, indicating learning was achieved successfully. DeepLabV3 has the strongest performance with a consistent and quick decrease in both training and validation loss, exhibiting good generalization and learning. U-Net performs well too but has slightly larger validation losses during the former epochs, but it manages to catch up during the later epochs. The nnU-Net model ultimately achieves reasonable performance but demonstrated more fluctuating performance through training (especially when validating) which may suggest that further tuning or regularization may be warranted. Overall, DeepLabV3 appears to be the strongest model with respect to reliable and stable performance

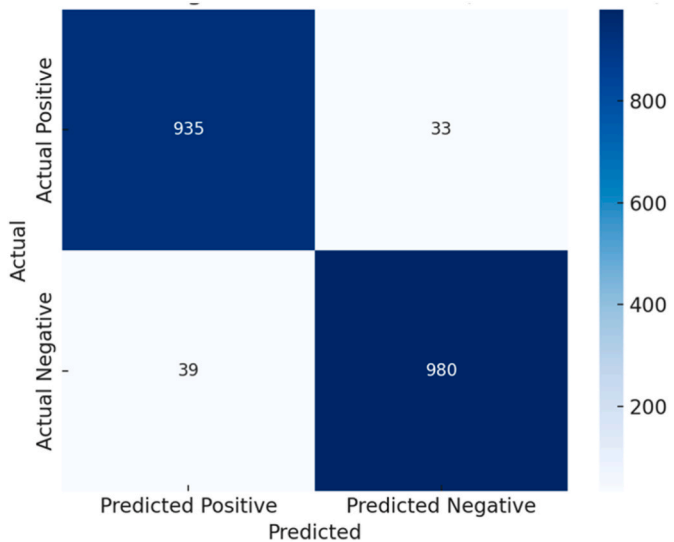


Fig. 13. Estimated average Confusion matrix for ref [124–154].

Table 13
Comparison of optimization methods in CNN-based brain tumor detection.

Model	Optimization Method	Accuracy (%)	Training Time	Overfitting
CNN (Baseline) [141]	Adam Optimizer	85.6 %	Fast	Mild
CNN + GA [51]	Genetic Algorithm (Hyperparameter Search)	89.2 %	Moderate	Reduced
CNN + PSO [69]	Particle Swarm Optimization (Weight Tuning)	91.1 %	Slower	Minimal
CNN + GA + PSO [127]	Hybrid (Feature Selection + Weight Optimization)	93.5 %	Longer	Best Generalization

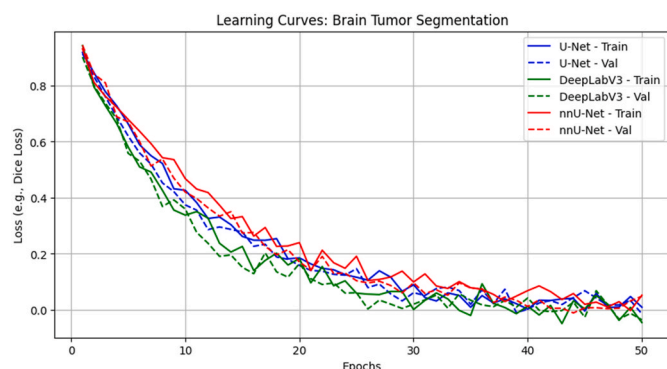


Fig. 14. Loss vs Epochs Learning Curves for Brain Tumor Segmentation.

for this segmentation style task.

3.7. Evaluation of research questions

In this section the findings of the research questions set will be analyzed.

3.7.1. Recent advances in MRI-based Techniques(RQ1)

Deep learning models like U-Net, ResNet, and DenseNet dominate recent developments related to MRI-based brain tumor segmentation. These architectures have been known for their strength in capturing complex spatial and contextual information. Techniques like 3D U-Nets and attention mechanisms have gone a step ahead to raise the bars of segmentation accuracy while managing the complexity of multi-dimensional MRI data. Hybrid approaches, integrating traditional and deep learning, such as hypercolumn techniques, have also been found to improve the robustness of the segment. The use of pre-trained models and transfer learning has also reduced training overhead and enabled higher performance, particularly when datasets are small.

3.7.2. Development of ML and DL models for brain tumor segmentation (RQ2)

Traditional ML methods include SVM and KNN, which have given way to deep learning architectures comprising CNNs, ResNet, and U-Net. The early ML models utilized handcrafted features, whereas DL models perform an end-to-end learning, hence explicit feature engineering is ruled out. Some of the superior variants to handle the spatial complexities of 3D MRI data include variants of CNNs, such as 3D CNNs and Attention U-Nets. The GANs and Transformers are new architectures being developed to solve these boundary accuracy challenges and data sparsity, thus showing that this evolution of DL models is not complete.

3.7.3. Limitations in ML/DL-based Methods(RQ3)

There exist significant challenges to the adoption of the ML and DL models for tumor segmentation in the brain. First, most models lack diversity in their datasets; the majority utilize standardized datasets like BraTS, hence limiting the models' generalization to other broader clinical applications. Whereas resource constraints are introduced by the computational complexity involved, especially in 3D architectures, annotated data remain one of the main bottlenecks, as labeling by experts is extremely time-consuming. Besides this, clinical trust and acceptance are obstructed by the "black box" nature of DL models. Different optimization techniques, semisupervised learning, generation of synthetic data, and XAI tools are developed in order to improve the interpretability and transparency of the results.

3.7.4. Role of datasets and metrics in model Performance(RQ4)

Datasets like BraTS and TCIA have driven recent advances in brain tumor segmentation. BraTS, in particular, is considered the gold standard by most studies due to the high-quality multi-modal MRI scans and

expert annotations therein. However, the lack of diverse datasets impacts the generalizability of models. Some of the most common metrics for the evaluation of segmentation accuracy and boundary precision include the Dice Similarity Coefficient and Hausdorff Distance. These metrics indicate that dataset quality and diversity play a huge role in model performance, pointing to the need for more diverse and comprehensive datasets if one hopes to achieve real-world applicability.

3.8. Practical applications and future research directions

1. Real-World Clinical Deployment:

Diagnostic Workflow Integration: Integrate AI models into hospital diagnostic workflows to support the interpretation of medical images by radiologists. For instance, AI algorithms can review MRI scans and identify areas indicative of tumors and indicate them as such, offering initial assessments to complement radiologists' readings. Integrating AI can automate the diagnostic process and cut back on time spent on accurate diagnoses.

Decision Support Systems: Design decision support systems based on AI that provide suggestions based on imaging data to support clinicians' informed decisions about patient care. The systems are able to limit diagnostic mistakes and enhance treatment planning by providing genuine and data-related information.

2. Scalability to Multi-Modal Imaging Data

MRI-CT/PET Scan Integration: Assess the efficacy of combining two or more imaging technologies, like MRI, CT, and PET scans, to increase tumor detection sensitivity. Multimodal imaging is able to produce complementary information and offer more detail in the tumor feature assessments. Its feasibility and usefulness can dictate whether it is possible to incorporate it into practice.

3. Federated Learning for Privacy-Preserving AI Diagnostics

Secure Multi-Hospital Collaboration: Explore federated learning methods allowing AI models to be trained on several hospitals without exchanging patient data. This will preserve patient anonymity but allow institutions to jointly refine diagnostic models across different datasets. Applying federated learning can make AI diagnostics more generalizable and reliable across populations and imaging modalities. The work [142] compares global, personalized, and hybrid federated learning methods to the Federated Brain Tumor Segmentation 2022 dataset. FedAvg works well, but some methods provide marginal improvement and mitigate bias from majority data distributions. This work also explores IID and few-data cases to shed light on federated learning behavior in medical imaging.

3.9. Challenges of AI-based brain tumor diagnosis

Even though AI algorithms have tremendous potential in brain tumor diagnosis, various significant hurdles need to be overcome before AI-based diagnosis comes into widespread clinical practice:

Regulatory Challenges: AI-based diagnostic technologies need proper validation and approval from organizations such as the FDA and EMA. Without a standard set of evaluation criteria, AI integration into clinical pathways is being held back.

Clinical Validation: Most AI models are trained from little amounts of data and may not necessarily undergo external validation against a wide range of patient populations. Real-world testing is required for validation to guarantee consistent performance across various hospitals and imaging environments.

Ethical Issues: MRI dataset bias can cause diagnostic accuracy variability across various demographic populations. Patient data privacy and security issues also need to be tackled while applying AI models

trained with sensitive medical data.

Interpretability and Trust: Clinicians require explainable AI models in order to be able to trust machine-based diagnoses. Techniques such as Grad-CAM and SHAP can help enhance model transparency, but there is more to be done in order to interpret AI decisions.

Federated learning and benchmarking: Federated learning, which allows model training to occur in a collaborative fashion across multiple healthcare institutions without the sharing of patient information. This method maintains confidentiality and enhances model generalizability through the use of heterogeneous datasets. The potential of federated learning, nevertheless, is limited by the absence of shared benchmark datasets and evaluation protocols. Data formats, labeling conventions, and performance metrics must have agreed-upon standards to enable reproducibility and meaningful comparison between studies.

Computational Costs: New architectures such as nnU-Net or Transformer models are very computationally expensive, preventing real-time diagnosis and scalability in low-resource environments. Model compression techniques such as pruning, quantization, and knowledge distillation are necessary for efficient deployment.

Model Overfitting and Limitations: Deep learning models tend to overfit, particularly when trained from small or biased data. They achieve high training accuracy and low generalization for unseen data. Regularization, cross-validation, and data augmentation are required to counteract this.

Dataset Imbalance and Generalization: Datasets available publicly tend to have a bias in the representation of tumor subtypes. This bias may cause models to favor more common tumor types at the expense of their efficacy on rare ones. Methods such as resampling, synthetic data augmentation, and federated learning are able to counter this restriction.

Overcoming these challenges is critical to ensure that AI-based MRI diagnostics are not just accurate, but also safe, fair, and clinically reliable.

4. Conclusion

Machine and deep learning for brain tumor diagnosis from MRIs. The current status of this paper was found after a thorough search using Brain Tumor, Diagnosis, MRI, machine learning, and deep learning. This study concentrated on brain tumor detection strategies using magnetic resonance images. After all of the categories were considered, 155 articles were selected for further analysis. The term "Brain Tumor, Diagnosis, MRI" appeared in the majority of the papers (about 64.50 percent) that were reviewed. Here is the breakdown of the number of articles for each of the search terms that were considered. 95 works in the field of DL and ML. Fig. 15 shows the number of papers by publication years.

The systematic review underscores the potential of ML and DL techniques to enhance the diagnosis of brain malignancies from MRI imaging. The assessment emphasizes the necessity for data diversity research, model interpretability, and computational efficiency. Future advancements in this field are likely to come from the development of

more robust models that can handle diverse datasets, feature extraction methods' advancement and computational methods' improvement. Overall, the application of ML and DL approaches has great potential to advance brain tumor treatment and early identification, which will eventually improve patient outcomes. Deep learning has enhanced brain tumor diagnosis, but key limitations must be addressed to achieve reliable AI models. Bias in MRI dataset selection affects performance because datasets like BraTS are likely to contain imbalanced tumor representation, leading to poor underrepresented class generalization. Scanner differences and domain shifts due to multiple hospitals can further reduce model robustness. Federated learning and domain adaptation can reduce these issues. The racial and demographic prejudices also carry risks, which necessitate balanced dataset formation to provide balanced model performance. Apart from bias, computational complexity is a barrier to real-time diagnosis. Demanding GPU requirements complicate deployment in a clinical environment. Pruning, quantization, and Edge AI platforms facilitate low-power device efficiency tuning. Latency constraints also limit real-time inference, while unexplainability compromises clinician confidence. Methods such as Grad-CAM, SHAP, and feature attribution support interpretability, thereby facilitating transparency and trust in AI diagnosis. All these barriers are pivotal to being addressed in guaranteeing clinical adoption.

CRedit authorship contribution statement

Vaidehi Satushe: Writing – original draft. **Vibha Vyas:** Conceptualization. **Shilpa Metkar:** Data curation. **Davinder Paul Singh:** Writing – review & editing.

Consent to participate

Informed consent was obtained from all individual participants included in the study.

Consent to publish

The authors affirm that research participants provided informed consent for publication of their data and all images included in the manuscript.

Future work recommendations for AI-based diagnosis of brain tumors

To further enhance AI-based brain tumor diagnosis, some directions need to be explored. Transfer learning methods can be employed to fine-tune pre-trained models for various tumor subtypes with fewer large labeled datasets and better generalizability across various MRI scans. This can aid in overcoming data insufficiency and enhancing classification accuracy for rare tumor types.

In addition, multi-objective optimization techniques need to be explored to optimize both model performance and interpretability. Although deep learning models have improved diagnostic performance, they tend to be difficult to interpret due to their complexity. Optimization procedures that take into account performance and simplicity simultaneously such as incorporating explainability constraints in training procedures can assist in creating AI systems that are effective and clinically reliable. With transfer learning and multi-objective optimization, the subsequent research can maximize the flexibility, efficiency, and applicability of AI models towards real-world use in healthcare.

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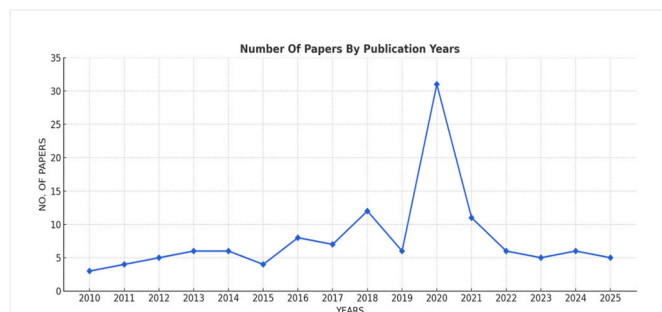


Fig. 15. Number of papers by publication years.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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