Journal of Applied Technology and Innovation
Vol. **09,** Issue 4, 2025**,** pp. **53-73**
e-ISSN:2600-7304-ISSN
DOI: https://doi.org/10.65136/jati.v9i4.35

State-of-the-Art Review and Future Directions in Artificial Intelligence-Based Detection of Brain Tumors Using MRI Datasets.

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Abstract

Brain tumors are increasingly common, and accurate diagnosis remains a challenge for clinicians. Magnetic Resonance Imaging (MRI) is a very common and efficient approach for detecting tumors, for this reason researchers apply several AI approaches for making the result efficient. Artificial intelligence (AI) offers a powerful solution to enhance detection accuracy and reliability. This study explores the overall AI methods for brain tumor detection using MRI brain tumor datasets. It highlights widely applied algorithms, including Machine Learning (ML), Deep Learning (DL), Federated Learning (FL), Knowledge Distillation (KD), and Large Language Models (LLMs). In addition to algorithms, this study reviews dataset sources such as BRATS, Kaggle, and real-world clinical data, along with their classification schemes (e.g., glioma, meningioma, pituitary, yes/no tumor). Imaging modalities beyond MRI, including CT and PET, are briefly noted for context. The paper further examines performance evaluation strategies, focusing on metrics such as accuracy, precision, recall, F1-score, sensitivity, specificity, and Dice coefficients. The innovation of this work lies in its integrated analysis of diverse AI approaches, dataset variations, and evaluation metrics, which together provide a comprehensive perspective missing in prior reviews. By comparing strengths and limitations across studies, the review identifies promising techniques and critical gaps in current research. Finally, the paper outlines future directions, including hybrid and multimodal AI frameworks, broader application of FL, KD, and LLMs. These insights aim to guide researchers, practitioners, and newcomers in advancing AI-based brain tumor diagnosis.

Keywords: *Brain Tumor, Artificial Intelligence, Machine Learning, Deep Learning, Federated Learning, Large Language Model.*

1. Introduction

Brain tumor is an unusual enhancement of tissue in the part of a brain (Amin et al., 2019). According to the Global Cancer Observatory (GCO) and the World Health Organization (WHO), brain tumors remaining 3-4% of all cancer-related deaths and 2-3% of all malignancies worldwide. In Bangladesh, brain cancer deaths are estimated to represent 1-2% of all cancer-related deaths, though reliable statistics remain scarce due to limited cancer registries. The mortality rate remains high because of difficulties in early detection, complex treatment procedures, and the limited effectiveness of therapies for certain tumor types. The most prevalent malignant brain tumors are Gliomas, glioblastomas, meningiomas. Most aggressive brain tumors are medulloblastomas, with glioblastomas which carry a five-year survival rate of only 5-10% (Rasool et al., 2024).

In hospitals CT, X-ray, PET, and MRI imaging modalities are applied to identify brain tumors. Among these, MRI is considered the most advanced and accurate modality (Kaifi, 2023). In the early 1900s brain tumors were visualized with X-rays and Angiography, but the starting of MRI in the 1970s which offers high-resolution, non-invasive imaging and enabling better monitoring during treatment. in the mid-20th century treatment approaches have also evolved significantly with radiosurgery and microsurgery for improving safety. Chemotherapy, radiotherapy, and precision medicine enhancing outcomes in recent era (Neamah et al, 2023). Despite these advancements, accurate tumor detection from MRI alone remains challenging (Alam et al., 2024; Rasool & Bhat, 2025; George et al., 2015; Choi et al., 2023; Rahimpour et al., 2021; Polas et al., 2023; Ullah et al., 2023). For this reason, researchers are increasingly applying AI approaches to enhance efficiency (Kanzawa et al., 2024; Kim et al., 2024; Gül & Kaya, 2024)**.** This review examines the studies of those works which are applying AI algorithms to MRI brain tumor datasets, suggests effective techniques, evaluates algorithmic limitations and offers future direction for brain tumor detection by applying AI techniques.

1.1. Types of Brain Tumor

The human brain contains three main parts: the cerebrum (forebrain), brainstem, and cerebellum (hindbrain) and is formed of millions of nerve cells. Cerebrum is the largest portion, consisting of the left and right hemispheres, which are connected by the corpus callosum (Sajid et al., 2019; Amin et al., 2022; Nalwade & Kisa, 2021). The brainstem, situated between the brain and spinal cord, includes the midbrain, pons, and medulla oblongata (Aleid et al., 2023; Naeem et al., 2022). The cerebellum, situated beneath the cerebrum at the back of the head, coordinates balance and movement. Figure 1 illustrates a brain with a tumor.

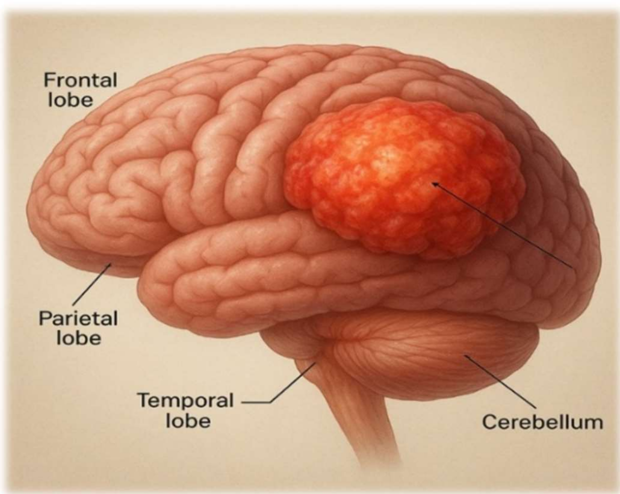

Figure 1: Anatomical regions of the human brain highlighting a tumor in the cerebrum.

There are noncancerous tumors, which grow slowly, called benign. Common examples include meningiomas, pituitary adenomas, schwannomas, and craniopharyngiomas (Lachinov et al., 2019; Gohari et al., 2024). Malignant tumors are cancerous, aggressive, and invasive. Most malignant brain tumors are gliomas, which include astrocytomas, glioblastomas, oligodendrogliomas, and ependymomas. Glioblastoma is considered the most aggressive, with poor survival outcomes (Islam et al., 2023; Zhou et al., 2024; Mahlool & Abed, 2022). Other malignant tumors include medulloblastomas, germ cell/pineal tumors, and chordomas/PNETs. The tumor which is growing to the other parts of the body but spread to the brain is called secondary tumor. These are more common than primary tumors. Table 1 presents the main tumor categories and representative examples.

Table 1: Classification of brain tumors with representative examples.

Tumor Category	Examples
Benign Primary Tumor	Meningioma, Pituitary Adenoma, Schwannoma, Craniopharyngioma, etc.
Malignant Primary Tumor	Gliomas (Astrocytoma, Glioblastoma, Oligodendroglioma, Ependymoma), Medulloblastoma, Germ Cell/Pineal Tumors, Chordoma/PNETs, etc.
Secondary (metastatic) Tumor	Tumors that are growing in another part of the body but spreading to the brain.

1.2. Imaging Modalities

Accurate imaging is essential for detecting brain tumors and for follow-up monitoring (Almadhoun & Abu-Naser, 2022; Sharma et al., 2014; Naeem et al., 2022). Several imaging modalities are commonly employed, each with unique strengths and limitations (Nair et al., 2024; Hemanth et al., 2019). Among them MRI produce more clear, understanding and high-resolution images. Gadolinium-based contrast agents are often used to improve the differentiation between tumor tissue and normal tissue (Kshirsagar et al., 2020; Anil et al., 2019). Computed Tomography (CT), although faster than MRI, provides less anatomical detail. It is particularly valuable in emergency situations, such as detecting hemorrhage or calcification, and when MRI is contraindicated (Zhao et al. 2024, Nazir et al., 2024; Khan et al., 2021). Magnetic Resonance Spectroscopy (MRS) technique analyzes the chemical makeup of brain tissue, making it effective for identifying tumor types and grading. Positron Emission Tomography (PET) evaluates the metabolic activity of brain tumors, aiding in tumor grading and recurrence detection (Saeedi et al., 2023; Srinivas et al., 2022; Rasool et al., 2022a; Rasool et al., 2022b). Table 2 represents the key points of different categories of imaging modalities.

Table 2: Comparison of major imaging modalities for brain tumor diagnosis and monitoring.

Modality	Key Features	Advantages	Limitations	Primary Applications
MRI	High-resolution structural imaging; contrast-enhanced with gadolinium	Gold standard for brain tumor detection; excellent soft-tissue contrast; non-invasive	Time-consuming; costly; contraindicated in patients with metal implants	Tumor detection, localization, treatment planning, monitoring progression
CT	X-ray–based cross-sectional imaging	Fast, widely available; useful in emergencies; good for detecting hemorrhage or calcification	Lower soft tissue contrast than MRI; radiation exposure	Initial screening, emergencies, when MRI is contraindicated
MRS	Chemical/metabolic profiling of brain tissue	Differentiates tumor types and grades; non-invasive biochemical insight	Limited spatial resolution; requires advanced MRI hardware/software	Tumor typing, grading, and assessing biochemical changes
PET	Functional imaging based on glucose or tracer uptake	Detects metabolic activity; useful for tumor grading and recurrence detection	Expensive; radiation exposure; lower spatial resolution	Grading tumors, recurrence detection, therapy response evaluation

Despite the growing number of studies in this field, there remains a gap in unified reviews that comprehensively address both traditional and emerging AI approaches for brain tumor detection. While earlier works primarily focused on classical ML and DL, limited attention has been given to newer techniques such as Federated Learning, Knowledge Distillation, and Large Language Models, as well as the critical role of Explainable AI in clinical adoption (Raza et al., 2022; Sharif et al., 2020a; Sharif et al., 2020b; Sharif et al., 2020c; Mohsen et al., 2018; Ansari, 2023). This review discusses the gap by systematically analyzing diverse AI techniques, dataset sources, imaging modalities, and performance metrics. By providing a holistic comparison, this work not only highlights state-of-the-art developments but also provides the problems and challenges and future opportunities for advancing AI-driven brain tumor diagnosis.

2. Literature Review

Numerous authors have been studying the application of AI techniques on MRI brain tumor dataset. analyzed studies employing ML models such as Random Forest (RF) and Support Vector Machine (SVM) and reporting the datasets like BARTS 2012–2021 (Amin et al., 2019). However, their work did not address Federated Learning (FL), Deep Learning (DL), or dataset class distributions. This review provided a broader review involving 28 DL algorithms, including CNN, VGG16, Inception-v3, MobileNetV2, and ResNet50 (Rasool et al., 2024). Despite this, the study did not consider Knowledge Distillation (KD), FL, or ML models, nor did it specify dataset sources. Both studies also lacked discussion on Explainable AI (XAI).

This work reviewed multiple AI techniques, focusing on tumor types (primary, secondary, malignant) and imaging modalities (PET, MRI, CT). Although CNN, SVM, and U-Net were discussed, dataset sources and advanced AI approaches were not explored (Kaifi, 2023). This study also emphasized MRI-based detection and classification, identifying several public datasets and listing DL algorithms applied between 2019 and 2021, yet also lack from other AI techniques and XAI (Neamah et al., 2023).
This work also examined AI frameworks, particularly CNNs and hybrid models, and highlighted the importance of XAI for interpretability and trust in clinical practice (Alam et al., 2024). Similarly, this study summarized ML and DL techniques for the classification of brain tumors but did not specify dataset sources or address XAI (Rasool et al, 2025). Table 3 provides a comparative summary of prior reviews, highlighting algorithms, dataset usage, classification methods, performance metrics, and graphical representations. It also demonstrates how this study extends existing work by incorporating ML, DL, FL, KD, LLMs, dataset analyses, and XAI to present a more comprehensive synthesis.

Table 3: Comparative summary of existing review studies on AI for brain tumor detection.

Paper	Methods	ML	DL	FL	KD	LLM	Data Sources	Class	Metrics	Figures/ Graphs	Comparative Analysis
(Amin et al., 2019)	12	✗	✓	✗	✗	✗	✓	✓	✓	✗	✓
(Rasool et al., 2024)	27	✓	✓	✗	✗	✗	✓	✓	✓	✓	✓
(Kaifi, 2023)	8	✓	✓	✗	✗	✗	✗	✗	✓	✓	✓
(Neamah et al., 2023)	15	✓	✓	✗	✗	✗	✓	✗	✓	✓	✓
(Alam et al., 2024)	5	✓	✓	✗	✗	✗	✓	✓	✗	✗	✓
(Rasool et al, 2025)	10	✓	✓	✗	✗	✗	✗	✓	✓	✗	✓
Current Study	30	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Legend: ✓ = included, ✗ = not included

3. Methodology

This review blends recent studies on brain tumor detection using artificial intelligence (AI). The methodology involves organizing existing works into those categories, several algorithmic approaches, dataset sources, dataset classification techniques, and the performance metrics for measuring the performance.

3.1. Taxonomy

The reviewed literature is organized into four main dimensions: (i) types of algorithms, (ii) dataset sources, (iii) dataset classification, and (iv) performance evaluation. The algorithms include ML, DL, FL, KD, and LLM. Publicly available MRI datasets like BRATS, Kaggle repositories, and clinical data archives are frequently used. Tumors are typically classified into glioma, meningioma, and pituitary types, while some works adopt a binary classification of "tumor" versus "no tumor." Figure 2 shows Taxonomy of this review showing algorithms, dataset sources, classifications, and evaluation criteria.

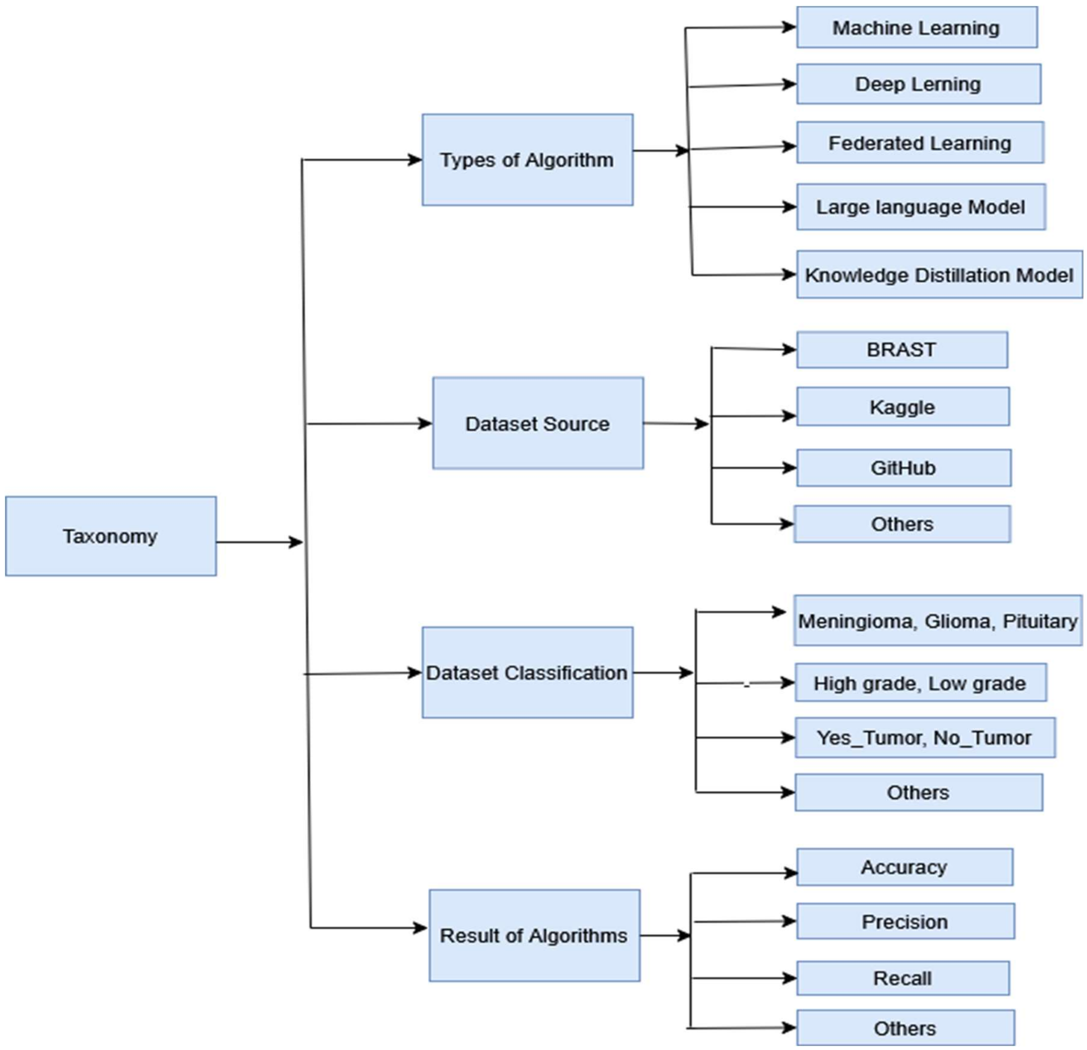

Figure 2: Taxonomy of this review showing algorithms, dataset sources, classifications, and evaluation criteria.

3.2. Artificial Intelligence Approaches

Artificial intelligence is the techniques of intellect of human into devices and preparing them to learn data and solve problems according to learning. In medical imaging, AI aims to design models that can be the alternative of human domestic or office work. Figure 3 illustrates the main families of AI algorithms applied to detecting brain tumors, namely Machine Learning, Deep Learning, Federated Learning, Knowledge Distillation, and Large Language Models (Polas et al., 2022). Within ML, commonly used algorithms include Random Forest, Naïve Bayes, Support Vector Machines (SVM), and C4.5 decision trees. DL approaches are dominated by CNN, U-Net, VGG16 and ResNet50. Some studies have also incorporated ensemble or hybrid DL strategies. Emerging methods such as FL ensure secure patient data, while KD focuses on reducing model complexity. Recently, LLMs such as BERT, ClinicalBERT, and RadBERT have been employed to process clinical notes and radiology reports related to brain tumors.

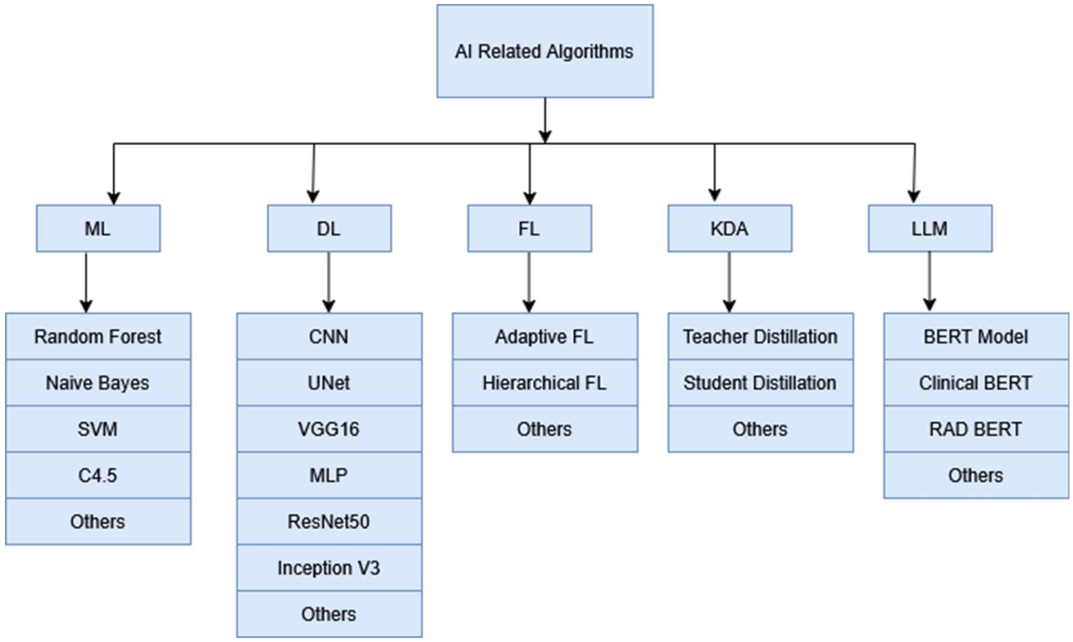

Figure 3: Categories of AI-related algorithms applied to brain tumor detection, including ML, DL, FL, KD, and LLMs.

A general workflow of AI-based for detecting tumors is presented in **Figure 4.** The process starts with the technique of preprocessing image, after preprocessing, features are extracted, and the dataset is divided into three subsets in which training and validation sets are used to build and optimize the model and testing set is reserved for final performance measurements. After selecting the best performance model, Explainable AI methods are applied to improve efficiency.

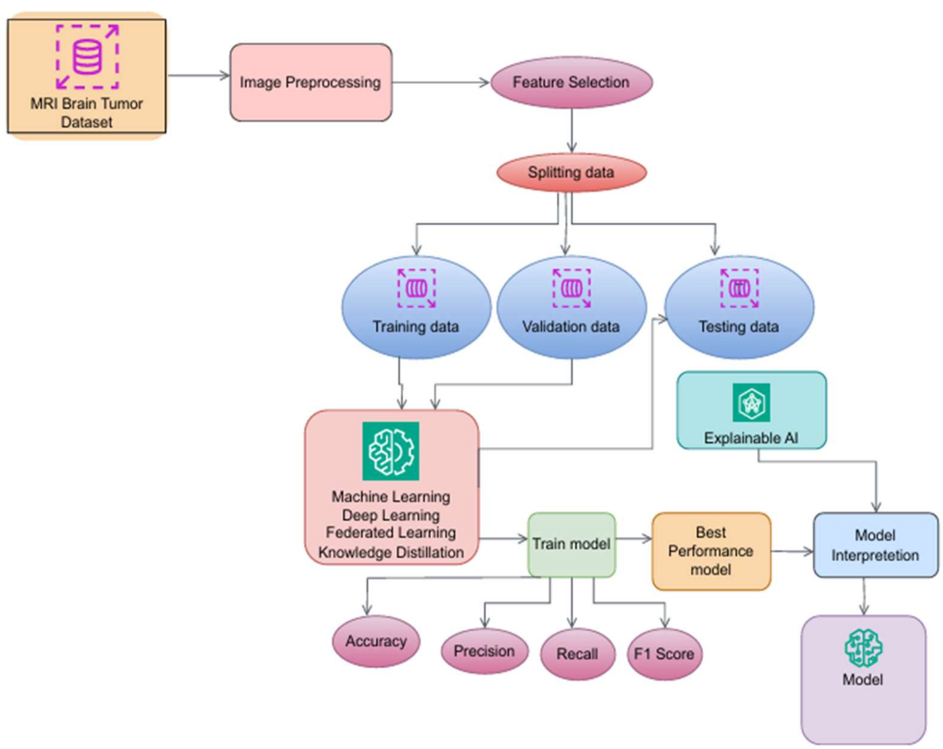

Figure 4: General framework of AI-based brain tumor detection, from preprocessing to evaluation and application of XAI.

3.2.1. Machine Learning

Machine Learning (ML) is a subdivision of AI that is used mainly for prediction techniques and improving the performance of the detection technique (Padma & Sukanesh, 2011; Ruba et al., 2020; Woźniak et al., 2023; Nanmaran et al., 2022; Khan et al., 2021; Özcan et al., 2021; Chen et al., 2017; Gupta et al., 2018a; Gupta et al., 2018b; Razzak et al., 2018; Karayegen & Aksahin, 2021).

3.2.1.1. Naive Bayes

The Naïve Bayes algorithm uses Bayes' theorem for assigning data to the class which has the maximum probability. For this reason, it is called probabilistic classifier. It performs well on real-world data due to its speed and robustness. In brain tumor research (Sharma et al., 2024) applied Naïve Bayes to a brain tumor dataset which has 210 MRI images. This model achieved 0.02s of training time and took 97.6s for completing classification.

3.2.1.2. K-Means

K-Means is a one kind of unsupervised ML algorithm that can classify data by grouping them into cluster according to their closeness. It is used no non-label data and find the similarity between data by calculating centroid (Sachdeva et al., 2013; El-Dahshan et al., 2010; Capra et al., 2020; LeCun et al., 2015; Dumoulin & Visin, 2016; Maqsood et al., 2022). Aleid et al., (2023) applied K-Means to the BRATS 2017 dataset and the accuracy was 57% with execution time of 45 seconds.

3.2.2. Deep Learning

Deep Learning (DL) is a subdivision of ML and AI which uses deep neural network or multilayered neural network and works with more complex data like image data (Anil et al., 2019). It is very useful in image processing, natural language processing and textual data [42]. It can process large image datasets and can be highly used on medical image data. Large image dataset can be processed by it and can be highly used on medical image data like brain tumor MRI images (Lamrani et al., 2022; Noreen et al., 2020; Segato et al., 2020; Alhasan, 2021; Yi et al., 2021).

3.2.2.1. CNN

CNNs are the most widely applied DL models for MRI-based tumor detection. Aleid et al. (2023) applied a CNN and reported 87% accuracy and Dice scores of 0.87 (Enhancing Tumor), 0.85 (Core), and 0.83 (Complete). Saeedi et al. achieved 96% training accuracy and 93% testing accuracy. Several other studies, including those by (Rafiq et al., 2022; Kaifi et al., 2023; Mahlool et al.,; Ullah et al., 2023; Hemanth et al., 2019) also demonstrated the effectiveness of CNNs. Figure 5 illustrates the architecture of CNN algorithm.

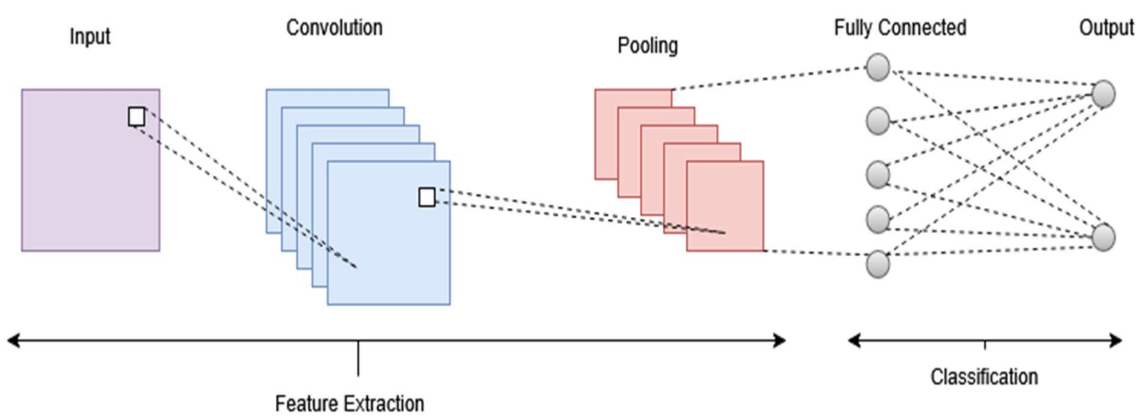

Figure 5: Structure of a CNN for tumor image analysis.

3.2.2.2. VGG16

VGG16 has 16 layers, convolutional layers contain 13-layers, pooling layer has 5 layers and fully connected layer has 13 layers (Han et al., 2020; Feng et al., 2020; Kamnitsas et al., 2016; Hamilton & Kernick, 2007; Galanaud et al., 2006). This model is widely used for classification because of its accuracy and simplicity. Rafiq et al. (2022) reported that applying VGG16 to a brain tumor dataset yielded 99.94% training accuracy, 99% test accuracy, 99.86% validation accuracy, and minimal training and validation losses. Similar success was presented by (Islam et al., 2023 and Mahlool et al., 2022) further validating VGG16's strong performance in brain tumor detection.

3.2.2.3. ResNet50

ResNet50 is part of the Residual Network family, designed to address challenges in training very deep neural networks. It consists of 50 layers and introduces shortcut lines that granted gradients to bypass one or more layers during backpropagation (Zacharaki et al., 2012; Macyszyn et al., 2015; Jain et al., 2014; Liu et al., 2016). In brain tumor studies, (Zhou et al., 2024) applied ResNet50 to a real dataset, achieved accuracy of 65.32% with a minimum loss of 1.017. In contrast, (Rafiq et al., 2022) reported stronger results on the BRATS dataset, with 98% test accuracy, 99.75% training accuracy, and 98.14% validation accuracy. Similar findings were presented by (Lachinov et al., 2019) confirming the model's suitability for tumor classification tasks.

3.2.3. Federated Learning

Federated Learning is an AI model that without exchanging secure data multiple devices or servers collaboratively trains a joint model. The model is trained by each device individually and communicates with the models results instead of transferring sensitive datasets to a server which is central. These methods make FL valuable in many sectors like healthcare, and mobile applications where data confidentiality is critical (Kshirsagar et al., 2020). Ullah et al. (2023) applied FL to the BRATS dataset and achieved 0.87, 0.90 and 0.95 in Dice Coefficient, Sensitivity and Specificity accordingly. This study also applied multiple deep learning techniques within the FL framework to improve performance. Similarly, (Islam et al., 2023) applied FL using VGG16 and InceptionV3 models. In their experiments, VGG16 achieved accuracies of 0.91 for the "no tumor" class and 0.95 for the "yes tumor" class. InceptionV3 also provided good results in the FL environment, reaching the accuracy of 0.95 for "no tumor" and 0.91 for "yes tumor." this study suggests that aplying DL algorithms on the FL environment provides the better result.

3.2.4. Knowledge Distillation Model

Knowledge Distillation (KD) is an AI approach in which a more accurate teacher model is replicated by a smaller efficient student mode. The teacher model is designed for the complex, pre-trained network with high accuracy and the student model is designed to be minimal and suitable for applying on devices with the computational resource limitation. During training, the student learns from the original dataset as well as from the teacher's outputs which capture the powerful information about class distributions (Lachinov et al., 2019). In brain tumor detection, without significantly sacrificing accuracy it is applied to improve efficiency. (Lachinov et al., 2019) investigated KD on a brain tumor dataset and found the result of validation 0.744 for Dice scores of ET, 0.922 for WT, and 0.884 for TC. Their method achieved Dice scores of 0.756 for ET, 0.905 for WT, and 0.842 for TC On an external validation set and for reducing computational complexity it demonstrates that distilled student models can maintain strong segmentation performance.

3.2.5. Large Language Model

Large Language Models are AI trained models which are vastly used on text data doors understanding human language. Models such as Generative Pretrained Transformers predict the next word in a sequence or generate coherent text using networks with billions of parameters. Their applications span machine translation, summarization, sentiment analysis, question answering, and conversational agents [28]. In brain tumor research, LLMs have been explored to analyze radiology reports and related clinical text. Kanzawa et al. (2024) and Zhao et al. (2024) applied BERT to the brain tumor datasets, achieving 97% accuracy, with specificities of 0.991, 0.993, and 0.958, and sensitivities of 1.000, 0.864, and 0.978 across three groups. Variants such as ClinicalBERT and RadBERT were also employed by (Zhao et al., 2024) yielding an AUROC of 86%. These results highlight the potential of LLMs to support diagnostic decision-making through effective interpretation of unstructured medical text.

Table 4 compares the number of algorithms applied on the MRI brain tumor dataset on the previous research. In Table 4, '✓' denotes 'Yes,' while 'X' signifies 'No.'

Table 4: Comparative analysis of algorithms applied to MRI brain tumor datasets in previous studies.

References	Random	K-Means	SVM	MLP	CNN	VGG16	VGG19	ResNet50	Inception V3	Hybrid	RNN	ANN	EfficientNetB	Distilled	Teacher	LLM Model	BERT Model	Clinical BERT	RadBERT
(Choi et al., 2023)	X	X	X	X	X	X	X	X	X	X	X	X	X	✓	✓	X	X	X	X
(Rahimpour et al., 2021)	✓	X	✓	X	✓	X	X	X	X	X	X	✓	X	✓	X	X	X	X	X
(Ullah et al., 2023)	X	X	X	X	✓	✓	X	X	X	X	✓	X	X	X	X	X	X	X	X
(Kanzawa et al., 2024)	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	✓	✓	X	X
(Kim et al., 2024)	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	✓	X	X	X
(Gül et al., 2019)	X	✓	✓	X	X	X	X	X	X	X	X	✓	X	X	X	X	X	X	X
(Amin et al., 2022)	X	X	X	X	✓	X	✓	X	X	✓	X	X	X	X	X	X	X	X	X
(Nalwade et al., 2021)	X	X	X	X	X	X	X	X	X	X	X	X	X	✓	✓	X	X	X	X
(Sajid et al., 2019)	X	X	X	X	✓	✓	✓	X	X	X	X	X	X	X	X	X	X	X	X
(Amin et al., 2022)	X	X	X	X	X	X	X	✓	X	X	X	X	X	✓	X	X	X	X	X
(Gohari et al., 2024)	X	X	X	X	X	X	X	X	X	X	X	X	X	✓	✓	X	X	X	X
(Islam et al., 2023)	X	X	X	X	X	✓	X	X	✓	X	X	X	X	X	X	X	X	X	X
(Zhou et al., 2024)	X	X	X	X	X	X	X	✓	X	X	X	X	X	X	X	X	X	X	X
(Mahlool et al., 2022)	X	X	X	X	✓	✓	✓	X	X	X	X	X	X	X	X	X	X	X	X
(Almadhoun et al., 2022)	X	X	X	X	✓	✓	X	✓	X	X	X	X	X	X	X	X	X	X	X
(Sharma et al., 2014)	X	X	X	✓	✓	X	X	X	X	X	X	X	X	X	X	X	X	X	X
(Naeem et al., 2022)	X	X	X	X	✓	✓	X	✓	✓	X	X	X	X	X	X	X	X	X	X
(Nair et al., 2024)	X	X	X	✓	✓	X	X	X	X	X	X	X	X	X	X	X	✓	✓	✓
(Hemanth et al., 2019)	✓	✓	✓	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
(Khirsagar et al., 2020)	✓	X	✓	✓	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
(Anil et al., 2019)	X	X	X	X	✓	✓	✓	X	X	X	X	✓	X	X	X	X	X	X	X
(Zhao et al., 2022)	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	✓	✓	✓
(Nazir et al., 2024)	X	X	X	X	✓	X	X	X	X	X	✓	X	X	X	X	X	X	X	X

Source: Authors' compilation, 2025.

3.3. Dataset Sources

Several publicly available MRI brain tumor datasets have been widely used in AI research. Some are annotated with binary labels, distinguishing between "tumor" and "no tumor." A representative sample of this type is presented in Figure 7.

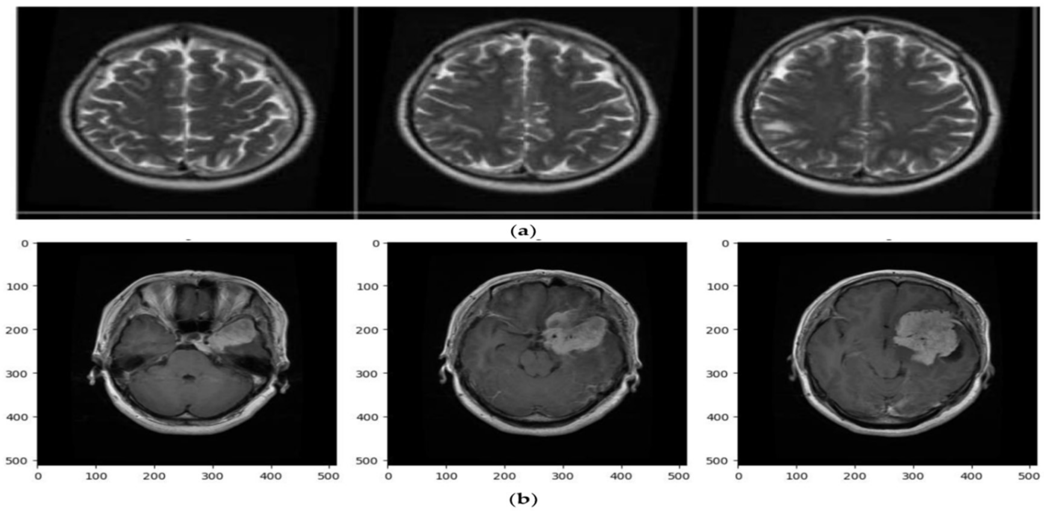

Figure 7: MRI brain scans labeled with binary classes (tumor vs. no tumor) (Smith & Doe, 2024)

Other datasets provide multi-class labeling, including glioma, meningioma, pituitary tumors, and health controls. **Figure 8** illustrates representative images from a four-class dataset before any preprocessing steps are applied.

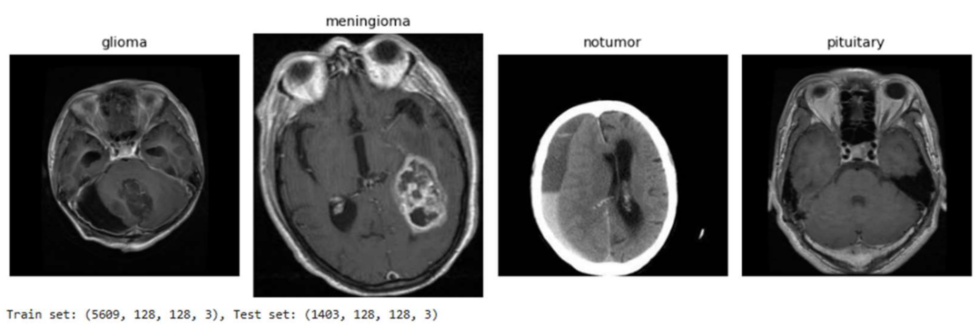

Figure 8: Representative multi-class MRI brain tumor images before preprocessing.

Sometimes images do not maintain good features. So, we need to increase the features and models performance some preprocessing methods such as normalization, noise reduction, contrast enhancement, and resizing are commonly applied. Figure 9 presents sample images after preprocessing, highlighting improvements in image clarity and uniformity.

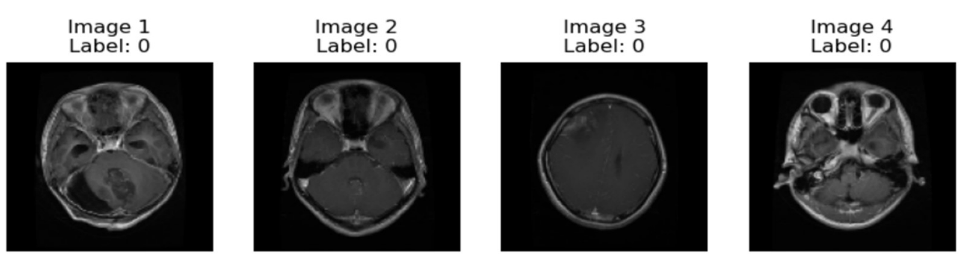

Figure 9: Brain tumor MRI dataset after preprocessing techniques including normalization, noise reduction, and contrast enhancement.

Some datasets also include multimodal MRI scans, providing complementary information through different imaging sequences. Common modalities include T1-weighted (T1), contrast-enhanced T1-weighted (T1w), T2-weighted (T2), and T2-FLAIR. A sample is shown in Figure 10.

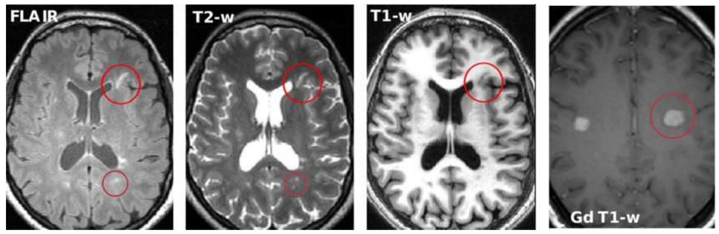

Figure 10: MRI brain tumor images from different models (Ma et al., 2021).

For model development, datasets are typically partitioned into three subsets:

Training set: The majority of the dataset applied to optimize model weights to learn input-output mappings.

Validation set: Applied to fine-tune hyperparameters, monitor overfitting, and guide model selection (Aleid et al., 2023). Cross-validation techniques such as k-fold partitioning are often employed for more reliable performance estimation (Gohari et al., 2024).

Testing set: Reserved for final evaluation to assess generalization ability on unseen data (Sharma et al., 2014).

In prior studies, different datasets have been employed. (Gul et al., 2024) used BRATS 2019–2021, while George et al. (2015), and Ullah et al. (2023) applied real-world clinical datasets. (Nalwade et al., 2021) utilized BRATS 2015 along with Kaggle datasets, and (Aleid et al., 2017) focused on BRATS 2017. Additional studies also incorporated data sourced from Kaggle and GitHub repositories.

3.4. Dataset Classification

Brain tumor MRI datasets have been categorized in multiple ways depending on the study objectives and dataset availability. (George et al., 2015) classified tumors into several types, including ependymoma, meningioma, lymphoma, cystic oligodendroglioma, anaplastic astrocytoma, and normal cases. (Ullah et al., 2023 & Islam et al., 2023) grouped tumors into high-grade glioma and low-grade glioma, reflecting clinical practice where glioma grading is critical for treatment planning. Other researchers adopted binary classifications such as “tumor” versus “no tumor” for simplicity and broader applicability. Table 5 summarizes the data set classification schemes reported across prior studies.

Table 5: Examples of dataset classifications used in prior brain tumor studies.

Dataset	Classes
Real data (George et al., 2015)	Ependymoma, Meningioma, Lymphoma, Cystic Oligodendroglioma, Anaplastic Astrocytoma, Normal
Kaggle, BRATS 2019 (Ullah et al., 2023)	Glioma, Meningioma, Pituitary gland tumors, Healthy brain
BRATS 2015 (Nalwade et al., 2021)	High-grade glioma, Low-grade glioma
Kaggle (Aleid et al., 2023)	Meningioma, Pituitary, Glioma
BRATS (Naeem et al., 2022)	Glioma, Meningioma
UK Data Service (Lachinov et al., 2019)	Tumor, No Tumor
BRATS (Islam et al., 2023)	High-grade glioma, Low-grade glioma

3.5. Performance Metrics

Several benchmarks are widely applied to compute the effectiveness of classification models. Accuracy is the most basic measure, the percentage of accurate predictions out of the total are represented by it. Although simple, it can be misleading when datasets are imbalanced. Precision measures the percentage of positively predicted outcomes which are positive. Recall or sensitivity and F1 score is also the benchmark of performance. Table 6 illustrates the algorithms and their corresponding results which are identified by several authors in their works.

Table 6: Algorithms applied to brain tumor datasets and their reported results

Studies	Algorithm	Reported Results
(George et al., 2015)	MLP	Instances: 173; Build time: 1.22; Classification rate: 95.2%
	C4.5	Instances: 173; Build time: 0.03; Classification rate: 91.1%
(Ullah et al., 2023)	Centralized Learning	Dice: 0.84; Sensitivity: 0.89; Specificity: 0.92
	Distributed Learning	Dice: 0.85; Sensitivity: 0.88; Specificity: 0.94
	Proposed FL Model	Dice: 0.87; Sensitivity: 0.90; Specificity: 0.95
	Federated Learning	Dice: 0.87; Sensitivity: 0.95; Specificity: 0.90
	U-Net	Dice: 0.83; Sensitivity: 0.88; Specificity: 0.91
	CNN	Dice: 0.82; Sensitivity: 0.87; Specificity: 0.93
	RNN	Dice: 0.76; Sensitivity: 0.81; Specificity: 0.89
	Other Neural Networks	Dice: 0.80; Sensitivity: 0.84; Specificity: 0.92
(Gül & Kaya, 2024)	FedBrainDistill (Teacher=2)	Round 10: IID=93.60%, non-IID=92.36%; Upload=0.11; Download=0.36
	FedBrainDistill (Teacher=10)	Round 10: IID=94.38%, non-IID=93.34%; Upload=0.29; Download=0.36
(Sajid et al., 2019)	2D CNN	Train Acc: 96.5%; Test Acc: 93.4%; Precision: 0.98; Recall: 0.97
	Convolutional Auto Encoder	Train Acc: 95.6%; Test Acc: 90.9%; Precision: 0.97; Recall: 0.97
(Aleid et al., 2023)	Single Path MLDeepMedic	Accuracy: 79%; Runtime: 6h
	U-Net	Accuracy: 80%; Runtime: 6h
	Rescue Net	Accuracy: 95%; Runtime: 6h
	Cascade Anisotropic CNN	Accuracy: 87%; Runtime: 5h
	K-Means + FCS	Accuracy: 57%; Runtime: 45s
	Multilevel HSO	Accuracy: 87%; Runtime: 2m
(Lachinov et al., 2019)	UNet	Dice ET=0.74–0.78; Dice WT=0.90–0.92; Dice TC=0.83–0.88
	Res UNet	Dice ET=0.74; Dice WT=0.92; Dice TC=0.83–0.87
	Cascaded U-Net	Dice ET=0.73–0.92; Dice WT=0.89; Dice TC=0.83–0.87
	Distilled Models	Dice ET=0.74–0.76; Dice WT=0.90–0.92; Dice TC=0.84–0.88
(Zhou et al., 2024)	EfficientNet-B0	Max Test Acc: 80.2%; Min Test Loss: 0.612
	ResNet-50	Max Test Acc: 65.3%; Min Test Loss: 1.017
(Mahlool et al., 2022)	Proposed CNN	Small-2c: Acc=0.87, Prec=0.85, Rec=0.89, F1=0.83. Large-3c: Acc=0.96, Prec=0.95, Rec=0.97, F1=0.94
	VGG 16	Small-2c: Acc=0.87, Prec=0.82, Rec=0.90, F1=0.88. Large-3c: Acc=0.93, Prec=0.89, Rec=0.97, F1=0.94
	VGG 16+SVM	Small-2c: Acc=0.55, Prec=0.85, Rec=0.41, F1=0.72. Large-3c: Acc=0.96, Prec=0.74, Rec=0.97, F1=0.96
	CNN in FL	Acc=0.87; Prec=0.82; Rec=0.85; F1=0.82
(Almadhoun et al., 2022)	Proposed Model	Train Acc: 100%; Val Acc: 98.3%; Test Acc: 98%
	VGG16	Train Acc: 99.9%; Val Acc: 99.9%; Test Acc: 99%
	ResNet50	Train Acc: 99.8%; Val Acc: 98.1%; Test Acc: 98%
	MobileNet	Train Acc: 99.8%; Val Acc: 89.0%; Test Acc: 88%
	Inception V3	Train Acc: 100%; Val Acc: 99.9%; Test Acc: 99%
(Sharma et al., 2014)	MLP	Samples: 210; Build time: 61.8; Classification time: 98.7
	Naive Bayes	Samples: 210; Build time: 0.02; Classification time: 97.6
(Nair et al., 2024)	Pituitary Adenoma	Samples: 253; Avg word count: 510
	Craniopharyngioma	Samples: 159; Avg word count: 532
	Meningioma	Samples: 141; Avg word count: 505
	Residual Tumor: Present	Samples: 51; Avg word count: 510
	Residual Tumor: Absent	Samples: 502; Avg word count: 564
(Hemanth et al., 2019)	Conditional Random Field (CRF)	Accuracy: 89%; Efficiency: 87.5%

Studies	Algorithm	Reported Results
	Support Vector Machine (SVM)	Accuracy: 84.5%; Efficiency: 90.3%
	Genetic Algorithm (GA)	Accuracy: 83.6%; Efficiency: 84.8%
	Convolutional Neural Network (CNN)	Accuracy: 91%; Efficiency: 92.7%

4. Findings

This part discusses the types of algorithms, dataset sources, dataset classification, and performance metrices.

4.1. Types of Algorithms

This work reviews the five types of AI algorithms: Machine Learning, Deep Learning, Federated Learning, Knowledge Distillation, and Large Language Models. Among these, Deep Learning is the most applied technique. After the most applied approach is Machine Learning, then used Federated Learning, Knowledge Distillation, and Large Language Models accordingly. Figure 12 illustrates the distribution of algorithm categories applied to the brain tumor dataset.

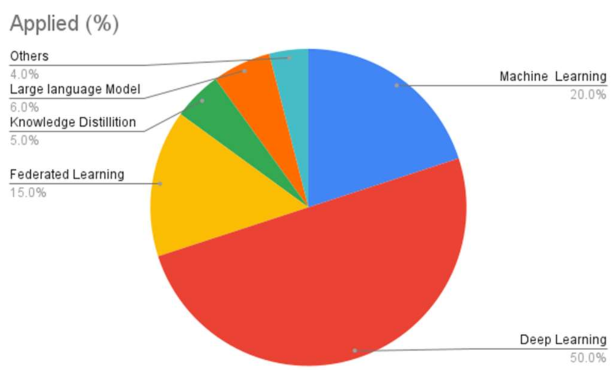

Figure 12: Distribution of algorithm categories applied in brain tumor detection research.

Within the ML domain, SVMs are the most frequently used, followed by Multi-Layer Perceptron (MLP). Other algorithms such as Naïve Bayes, C4.5, KNN, and Random Forests, are also employed but less frequently. **Figure 13** presents the relative frequency of ML algorithms reported in the reviewed studies.

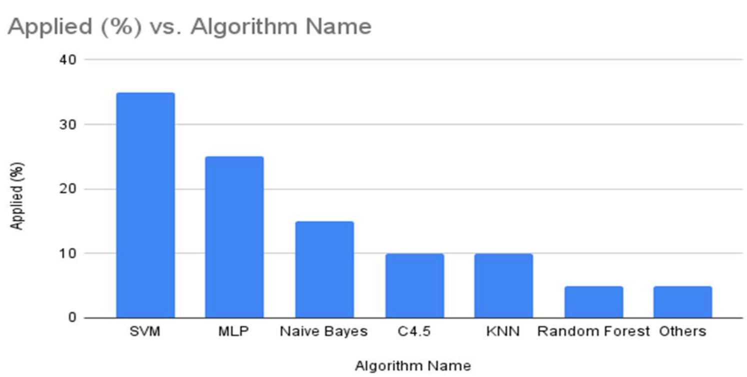

Figure 13: Frequency distribution of Machine Learning algorithms applied to brain tumor detection.

Deep Learning approaches dominate the field, with CNN being the most prevalent, followed by architecture such as VGG16 and ResNet50. Additional models, including Inception V3, Cascade U-Net, basic neural networks, and hybrid frameworks, appear in fewer studies. Figure 14 summarizes the frequency of DL model usage.

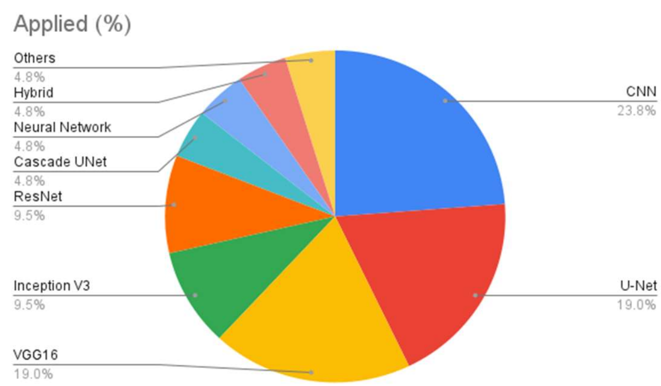

Figure 14: Frequency distribution of DL models applied in brain tumor detection.

For Federated Learning, EfficientNetB0 is the most reported architecture, though a variety of alternative FL models have also been tested in distributed environments. **Figure 15** shows the distribution of Federated Learning models in the reviewed literature.

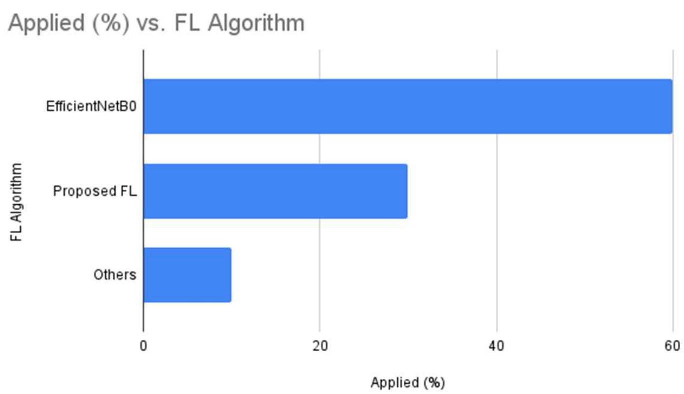

Figure 15: Frequency distribution of Federated Learning models applied to brain tumor datasets.

In the case of Knowledge Distillation, FedBrain Distilli emerges as the most frequently employed framework, followed by teacher; student model designs. Distilled student models are also reported, though with less frequency. **Figure 16** represents the distribution of KD models.

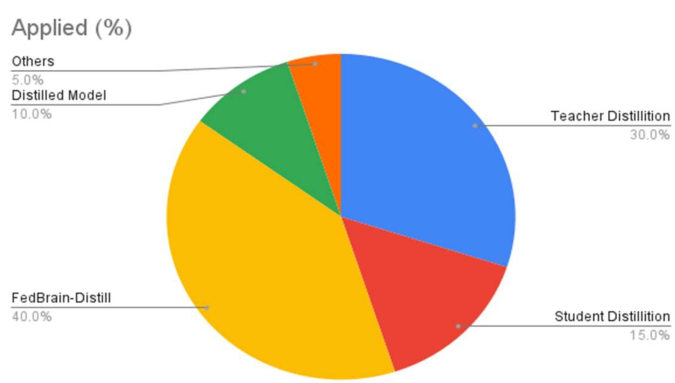

Figure 16: Frequency distribution of Knowledge Distillation models used in brain tumor detection research.

Finally, within Large Language Model category, BERT is the most widely applied, followed by ClinicalBERT. Other variants, including RAD-BERT and fine-tuned pretrained BERT models, have been adopted in a very few studies. **Figure 17** provides an overview of LLM applications.

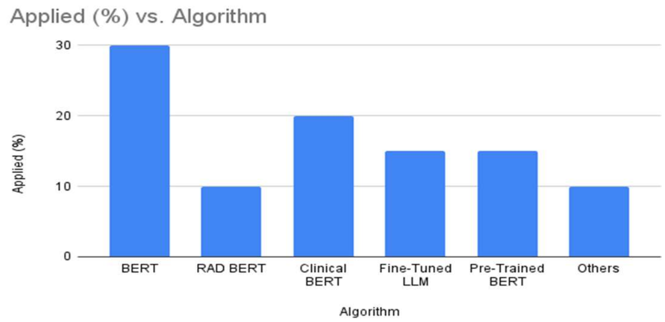

Figure 17: Frequency distribution of Large Language Models applied to medical text and imaging reports for brain tumor analysis.

The comparative overview represents the clear dominance of DL approaches, particularly CNN-based models, while also demonstrating the growing interest in federated and distillation-based frameworks as solutions for data privacy and efficiency in clinical AI research.

4.2. Dataset Sources

Analysis of prior studies shows that the BRATS (Brain Tumor Segmentation) datasets, particularly those spanning 2013 to 2021, are used most of the time in detecting brain tumors. Their popularity stems from standardized annotations, multimodal MRI scans, and annual benchmarking challenges that make them highly suitable for model development and comparison. Kaggle brain tumor datasets are also frequently employed, often in combination with BRATS to enhance dataset diversity. In addition, several studies utilize real-world clinical datasets, though these are typically smaller in scale and sometimes integrated with publicly available sources to improve robustness. GitHub repositories and other online collections are used less often and generally serve as supplementary sources rather than primary datasets. Figure 18 presents the distribution of dataset sources, highlighting the dominance of BRATS, followed by Kaggle and real clinical data, with GitHub and miscellaneous sources contributing a much smaller proportion.

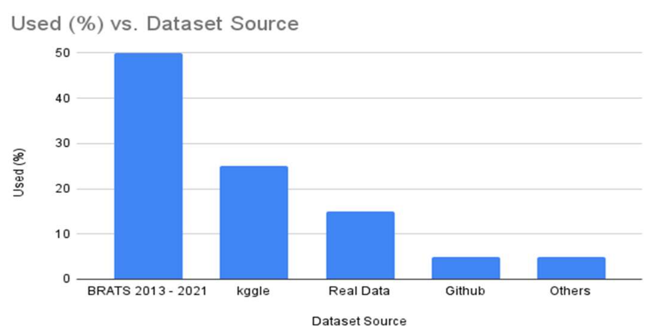

Figure 18: Frequency distribution of dataset sources used in brain tumor detection studies.

4.3. Dataset Classification

In the reviewed studies, the most common classification scheme divides brain tumors into meningioma, glioma and pituitary tumor categories, reflecting the prevalence of these tumor types in clinical practice. Several studies further refine this categorization into intermediate and severe gliomas, which is clinically important treatment planning and prognosis. Simpler binary classification approaches, such as tumor vs. no tumor, are also frequently employed, particularly in studies focusing on detection rather than subtype differentiation. Other less common classifications include rare tumor types and mixed categories. Figure 19 illustrates the distribution of dataset classification approaches, highlighting the dominance of the glioma-meningioma-pituitary framework, followed by glioma grading schemes, binary tumor detection, and other minor groupings.

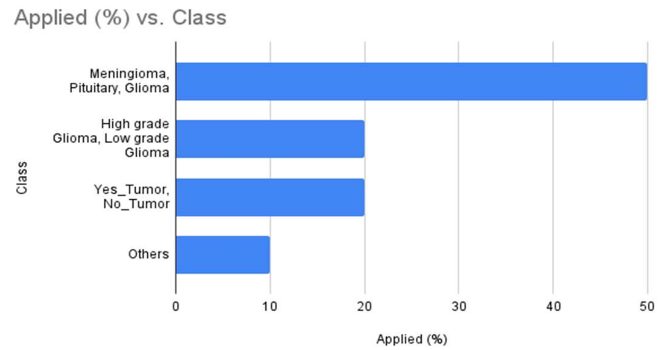

Figure 19: Frequency distribution of dataset classifications applied in brain tumor detection studies.

4.4. Performance Metrics

The evaluation of brain tumor detection models relies on a variety of performance metrics, with accuracy being the most widely reported. In most studies, accuracy is presented in two forms: training accuracy, which reflects model learning, and testing accuracy, which indicates generalization performance on unseen data. Beyond accuracy, precision and recall are frequently employed to provide higher perception into model reliability. Precision means the percentage of accurately identified tumor cases among all predicted positive cases and recall (sensitivity) means how many actual tumor cases are correctly detected. Specificity is also considered in many studies to assess the capability of models to accurately identify non-tumor cases. Furthermore, segmentation-focused research often incorporates Dice similarity metrics (such as Dice WT, Dice ET, and Dice TC), which are particularly valuable in evaluating region-level prediction quality. Figure 20 illustrates the distribution of performance metrics reported in the reviewed works, emphasizing the dominance of accuracy, followed by precision, recall, and other specialized measures such as sensitivity, specificity, and Dice scores.

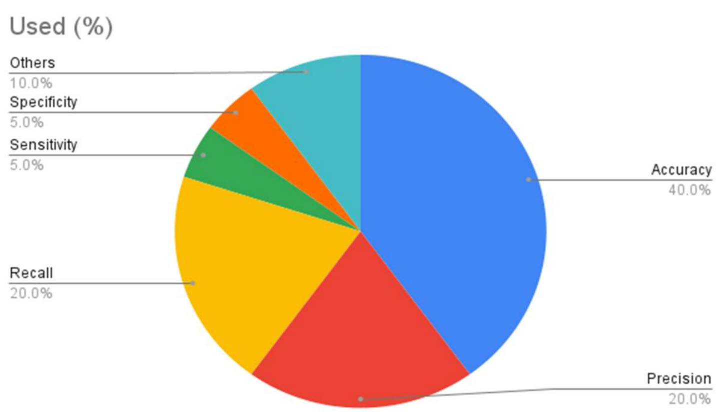

Figure 20: Frequency distribution of performance metrics used in brain tumor detection research.

4.5. General Problems and Challenges

The employment of ML and DL models to the brain tumor datasets ca faces some problems. First, the images cannot be suitable for the AI models, for this reason some preprocessing techniques like noise reduction, image resizing, contrast enhancement and others need to be applied to the images for enhancing the image quality. Some tuned techniques can eliminate the features of the images so, when applying this technique researchers need to be careful. Secondly, for applying DL model we need large memory capacity, advanced GPUs and more advanced device. It is a big challenge for the new researchers, hospitals and institutions. Thirdly, Sometimes the knowledge gap like when extracting feature researchers often extract inaccurate feature and it is a big issue for dealing with the DL algorithms and it provides the wrong result. Finally, despite the use of advanced approaches such as Federated Learning, Knowledge Distillation, and Explainable AI, there is still no accurate approach that works best in all datasets in all environments. Moreover, the limitation of clinical validation of AI systems in real-world healthcare is delaying their adaptability into accurate diagnostic practice.

4.6. Recommendation

By using high quality MRI brain tumor images researchers can get more acquiring results. Some preprocessing techniques like noise reduction, image resizing, normalization and other techniques can be used for getting more interpretable images. Researchers can use the CNN algorithm on the FL environment and some KDD model like Teacher distillation and Student distillation model to the MRI dataset. Explainable AI can be applied as the best performing AI model for making the system more interpretable and trustworthy. For segmenting the tumor data and extracting features CNN can be applied which provides higher accuracy. Researchers can use this algorithm on the several MRI brain tumor datasets which are collected from several sources and the datasets which have different classes.

4.7. Future Direction

In future for detecting brain tumor from MRI images researcher can benefit from broader accumulation of Federated Learning (FL), Large language Models (LLM) and Knowledge Distillation (KD) approaches. In the case of large-scale datasets FL provides privacy and work cooperatively with multiple institutions without sharing patient data. By integrating MRI with other imaging techniques PET and CT scan or hybrid approaches like combining MRI with T1, T2, FLAIR and contrast enhancing future progress can be achieved. These techniques can provide higher accuracy and better brain tumor detection methods. For more precise prediction multimodal DL technique can be used for handling hybrid data. When the data is limited, Transfer Learning can be a significant opportunity because its pre-trained model is used on specialized datasets. After finding a more accurate model researcher can use the Explainable AI model as the best performer model for making the output more interpretable and trustworthy.

5. Conclusion

Brain tumors represent unusual enhancements within brain tissue that disrupt the normal functioning of the nervous system. The primary goal of applying Artificial Intelligence (AI) to MRI datasets is to increase the accuracy of tumor detection, thereby supporting clinical decision-making. This review examined 74 studies and organized the discussion into four major areas: algorithm types, dataset sources, dataset classifications, and performance metrics. In terms of algorithms, Deep Learning has emerged as the most dominant approach, with CNNs being the most widely applied. Machine Learning methods continue to play a supportive role, while Federated Learning, Knowledge Distillation, and Large Language Models remain underexplored yet promising areas for future research.

With respect to datasets, the BRATS collection is the most extensively utilized due to its standardized annotations and widespread availability, whereas GitHub-based datasets are rarely employed. Classification schemes most often focus on meningioma, glioma, and pituitary tumors, with some studies adopting binary labeling such as “tumor” versus “no tumor.” For performance evaluation, accuracy is the most frequently reported metric, while specificity and Dice-based measures are less commonly used despite their clinical value in segmentation tasks. This study also discussed the brain tumor types and the importance of imaging mode like MRI, CT, and PET in giving easy diagnostic system. By blending the findings from existing works, this review not only presents the robustness of current AI-based methods but also points to underexplored directions. The collaboration of advanced approaches such as Federated Learning, Knowledge Distillation, and Explainable AI could significantly enhance trust, scalability, and clinical applicability. Overall, applying AI techniques to MRI brain tumor datasets demonstrates considerable potential to advance diagnostic accuracy and represents a practical step toward modernizing medical imaging in clinical practice.

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