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A Review on Multi-Class Brain Tumor Detection and Classification: Trends and Future Directions

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Abstract— The brain tumor classification is crucial to timely detecting patients and planning effective treatment. Multi-class brain tumor analysis does not merely recognize the presence of a tumor but tries to separate among various forms of tumors, including glioma, meningioma, and pituitary adenoma. The subjective interpretation of MRIs by hand has been known to be subjective, tedious and prone to human error. Modern advancements in deep learning (DL) and machine learning (ML) have improved the precision and reliability of the automation of diagnosis of brain tumors significantly. Traditional ML models such as SVM, KNN and Random Forest make use of hand crafted features, whereas modern DL models, specifically ConvolutionalNeuralNetworks (CNNs) can extract high-level spatial features in medical images automatically and thus perform better in classification. Recent developments like transfer learning, Vision Transformers (ViT), Explainable AI (XAI) and Federated Learning are moving towards more interpretable, privacy protecting and generalizable diagnostic models. This work is a comprehensive look at imaging methods, classification, current trends, challenges, and future trends in the analysis of multi-class brain tumors. Explainable frameworks, lightweight models, and large, multi-institutional datasets are required for real-time clinical deployment, according to the research, in order to improve the diagnostic procedures' accuracy and dependability.

Keywords— Brain Tumor Classification, MRI Imaging, Machine Learning, Deep Learning, Convolutional Neural Network (CNN), Explainable Artificial Intelligence (XAI), Federated Learning.

Introduction

Brain tumors are considered to be one of the worst neurologic diseases, which usually leads to severe cognitive and physical impairment, in case of late diagnosis. Due to its non-invasive nature and excellent soft tissue contrast, MRI has maintained its position as the imaging method of choice for the diagnosis of brain malignancies [1]. The issue is that distinguishing among various types of tumors takes much time and is prone to inter-observer error when the MRI data are not interpreted manually. The growth of automated mechanisms that can detect and categorize brain cancers to a significant degree is, therefore, helpful in clinical decision-making. This necessity has prompted researchers to concentrate on multi-class brain tumor classification. The objective is to distinguish between the most prevalent forms of brain cancer, such as gliomas, meningomas, and pituitary tumors. Multi-class classification must consider subtle variations in tumor form, texture, and location unlike binary classification which only determines the presence or absence of a tumor. This complexity is inefficient in conventional machine learning methods, which are based on features[2]. Consequently, the capacity of DL, and in particular CNNs, to directly learn discriminative features from imaging data has drawn a lot of interest.

Based on the achievements of CNN-based models, newer designs such as MobileNet and EfficientNetB7 have been promising. EfficientNetB7 operates under the concept of compound scaling so as to optimize accuracy and maintain computing efficiency and hence is favored in high-resolution MRI data. MobileNet, on the contrary, employs depthwise separable convolutions to conserve the cost of computing, which can be implemented in clinical practice with a modest resource base or in real time. The growing popularity of such architectures is indicative of a definite movement toward the performance-practicality balance in medical AI.

In spite of these developments, there are still evident problems, especially with the imbalance of the datasets, the inconsistency of MRI acquisition settings across facilities, and the inability to guarantee the model generalization. The predictions by most of the high-performing DL models lack clear visual or clinical interpretability, thereby rendering them black boxes [3]. Clinical adoption requires transparency, and, therefore, there is an urgent need to address explainable and reliable AI.

The purpose of this research article is to provide a comprehensive analysis of the current state of multi-class brain tumor detection and classification as well as potential future directions for growth in this area. The paper will demonstrate how the field has been shifting to clinically viable, interpretable, and efficient diagnostic support systems through the analysis of the available and accessible data sets, deep learning processes, model performance, current issues, and innovations.

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Structure of the paper

The paper is structured as follows: **Section II** explains the fundamentals and imaging modalities used in brain tumor detection. **Section III** discusses traditional ML and DL classification approaches. **Section IV** outlines future directions emphasizing dataset expansion, multimodal integration, and lightweight models. **Section V** summarizes the paper's significant results and future research potential.

Fundamentals of Multi-Class Brain Tumor Analysis

Multi-class brain tumor analysis is concerned with separating between different types of tumor as opposed to just the presence or absence of a tumor. The significance of this is that brain tumors including glioma, meningioma, and pituitary adenoma differ greatly in regard to their biological behavior, treatment, and prognosis[4]. Radiologists' subjective and time-consuming interpretation of MRI data has historically served as the basis for clinical diagnosis. With the current growth of MRI scans in clinical practices, there is an increased demand of automated systems that will be able to carry out reliable multi-classification to aid clinical decision-making.

Imaging Modalities in brain tumor

Several medical imaging techniques have been used in the identification of brain abnormalities. Structural and functional imaging are the two methods used to study the brain. Structural imaging is a collection of measures that pertain to the architecture of the brain, the location of tumors, injuries, and other brain disorders. The visual depiction of brain activity, smaller-scale metabolic alterations, and lesions may all be captured by functional imaging methods. The size, location, shape, and other characteristics of brain tumors may be determined using a number of imaging modalities, including CT, MRI, SPECT, FMRI, and ultrasound (US).

MRI: The MRI technique does not need incisions but rather the use of nonionizing, nonharmful radiation to reveal the three-dimensional architecture of any bodily region. To capture pictures, it uses radio frequency pulses and a powerful magnetic field. Differences between CSF and brain abnormalities may be distinguished using FLAIR. An MRI scan produces a picture by transforming grayscale intensity data into pixel spaces. The density of the cells determines the gray-level intensity values. Different tumorous tissues have different intensities on T1 and T2 brain imaging. Figure 1 displays it.

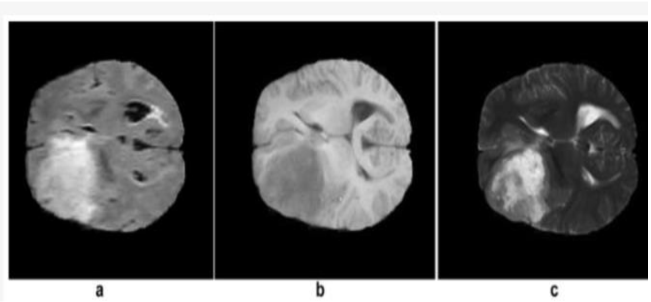

Figure 1: MRI brain tumor (a) FLAIR image (b) T1 image and (c) T2 image

CT-Scan: An X-ray beam that rotates through a network of detectors in a CT scanner may provide very detailed images of an organ or tissue's internal structure. The whole body may be captured in cross-sectional images by using certain algorithms on a computer to analyze images shot from various angles. Conventional practice dictates that patients get contrast injections to highlight aberrant tissues, as seen in Figure 4. Occasionally, the patient may be asked to take dye in order to enhance their picture. Figure 2 indicates that a CT scan may be used to identify a brain tumor in cases when an MRI cannot be conducted due to the patient's implantation, such as a pacemaker.

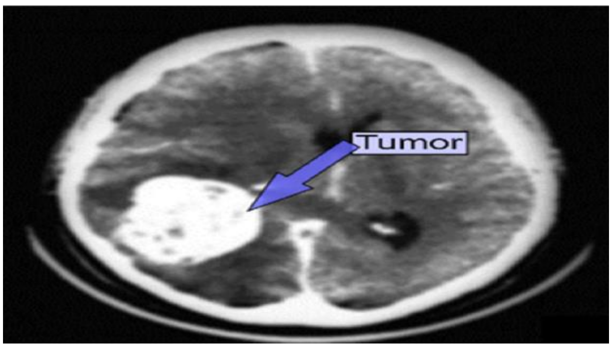

Figure 2: CT Brain tumor

PET-Scan: The PET technique may image metabolic processes in living tissues by directing a scanning beam of light from a radionuclide to a precise area inside the organ or tissue of interest. In order to help in the assessment of the

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investigated tissue, a little amount of a radioactive tracer is employed throughout the procedure. Among the several PET agents available, fluorodeoxyglucose (FDG) is useful for brain imaging. For a more conclusive picture of tumors and other anomalies, including cancerous ones, PET may be combined with additional diagnostic tools like CT or MRI, as shown in 3.

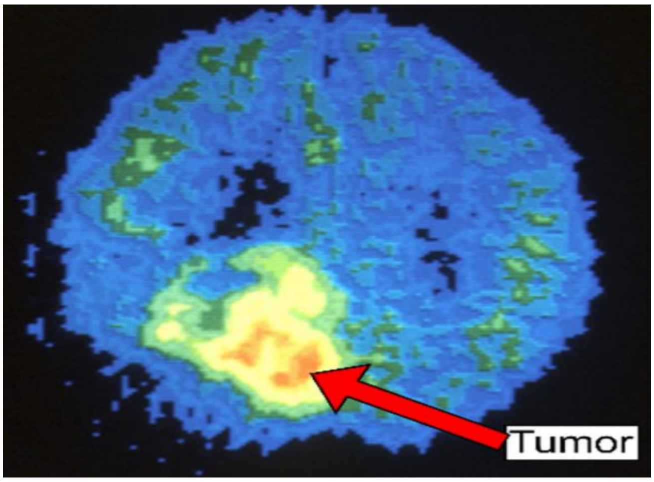

Figure 3: PET brain Tumor

SPECT: Radioactive tracers are used in nuclear imaging exams known as SPECT. Medical personnel are able to monitor blood flow to organs and tissues because of the tracer. The patient is given a tracer to inject into their bloodstream prior to the SPECT scan. The gamma rays produced by the radiolabeled tracer are detectable by the CT scanner because of its radiolabed nature.

Ultrasound: A specialized imaging method called an ultrasound may reveal information that is helpful in the detection of cancer, particularly when it comes to soft tissues. It is often administered as the first step in the conventional method of cancer diagnosis. Because solid masses bounce sound waves differently than fluid-filled cysts, an ultrasound may identify tumors that may be cancerous.

The table below compares several medical imaging modalities used to diagnose brain tumors.

Table I: Comparison of Medical Imaging Techniques for Brain Tumor Diagnosis

Imaging Technique	**Principle / Working**	**Radiation Type Used**	**Contrast Agent / Tracer**	**Advantages**	**Limitations / Disadvantages**
MRI (Magnetic Resonance Imaging)	Produces precise three-dimensional pictures of the body by aligning hydrogen atoms using powerful magnetic fields and radio frequency pulses.	Non-ionizing radiation (magnetic field & radiofrequency)	Gadolinium (optional)	Excellent soft-tissue contrast; no ionizing radiation; detects structural and pathological changes	Expensive, takes more time to scan, and isn't safe for those who already have metal implants.
CT Scan (Computed Tomography)	Generates cross-sectional pictures of the body by use of X-ray beams and detectors that spin.	Ionizing radiation (X-rays)	Iodine-based contrast dye (optional)	Fast, widely available, useful for bone and calcification	Radiation exposure; less soft-tissue contrast; may require contrast dye
PET Scan (Positron Emission Tomography)	Detects gamma photons emitted from radionuclide decay to map tissue metabolism.	Ionizing radiation (gamma rays)	Radioactive tracer (e.g., FDG)	Shows tumor metabolism and malignancy level; detects recurrence	Poor spatial resolution; expensive; radioactive exposure
SPECT (Single Photon	Combines CT imaging with gamma-emitting tracer to visualize blood	Ionizing radiation (gamma rays)	Gamma-emitting	Shows regional blood flow; complements	Lower resolution than PET; radioactive tracer

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Emission Computed Tomography)	flow.		tracer	MRI/CT	required
Ultrasound	Uses high-frequency sound waves reflected from tissues to form images.	No radiation (sound waves)	None	Safe, non-invasive, low cost, real-time ima	

Multi-Class Brain Tumor Classification Approaches

The term "computer-aided detection and diagnosis" describes software that analyzes images from radiology and pathology using DL, ML, and computer vision. The purpose of its creation is to help radiologists diagnose human diseases in different parts of the body, including brain tumors.

Classification Method

Datasets with similar characteristics are placed together in a classification. A classifier is a model in the area of classification that may be utilized to forecast the different properties of a class label [5]. To assign a predicted class to each input data point is the fundamental goal of classification. Medical picture categorization is done using ML and DL approaches. The key distinction between the two types is the approach used to collect the attributes needed for categorization.

1. Machine Learning

ML is a subfield of AI that enables machines to acquire new knowledge without human intervention. Classifying medical images, including lesions, into various groups using input features is one of the latest applications of ML. Supervised learning and unsupervised learning are the two main categories of ML algorithms [6]. ML algorithms are trained in supervised learning using data that has been labeled. By using unlabeled data, ML systems engage in unsupervised learning, which aims to understand the interdata connection. Brain cancers have been studied using ML in the context of brain imaging. Preprocessing images, extracting features, selecting features, and finally classifying them are the primary steps in ML classification. The process architecture is shown in Figure 6.

- Dataset: Collect pictures of brain cancer using several imaging modalities. As previously stated, we may get brain cancer pictures utilizing a variety of imaging modalities, including MRI, CT, and PET. This approach successfully depicts the abnormal brain.

- Data-preprocessing: One crucial step in the medical industry is preprocessing. Typically, preprocessing is when photos are enhanced or reduced for noise. Medical noise drastically reduces image quality, making them useless for diagnosis. To properly classify medical images, the preprocessing phase must be able to effectively eliminate large volumes of noise without compromising essential image components. Feature extraction: The process of "feature extraction" is used in medical imaging to convert unprocessed images into valuable data based on a variety of important characteristics. These characteristics are completely distinct from the original photos, but they convey the same information.

- Feature selection: This method makes an effort to rank the characteristics from most important to least, with the top features being used for categorization the most.

Traditional Machine Learning-Based Classification

There are some machine learning classifications are as below:

Classifiers: SVM, Random Forest, K-NN, Naive Bayes

A brief overview of each classification method utilized in the proposed study is provided in this section [7].

- SVM: The SVM is a well-known classifier used for regression and classification. SVM offers a variety of kernel functions for mapping low-dimensional to high-dimensional space in an SVM model. The findings of this investigation were obtained using the RBF kernel, which is detailed in the next section.
- LightBoost: An effective gradient boosting system, LightGBM stands for Light Gradient Boosting Machine and does quite well on classification problems. The algorithm builds decision trees in a leaf-wise fashion, aiming for the leaf that reduces loss the most. Comparing this approach to level-wise expansion, it improves efficiency. A histogram-based technique is also used by LightGBM to expedite the training process.
- KNN: An easy-to-use but powerful method for classification problems is KNN. It uses the majority voting concept among the feature space's k closest neighbors. When a new data point is introduced, KNN uses a distance measure, usually Euclidean distance, to determine the k most comparable instances from the training dataset. Among these neighbors, the majority class determines the categorization.

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- Adaboost: In this work, we suggested using an Adaboost model based on DT, which leverages the fundamentals of DT as a core classifier and also uses Adaboost for weight updates, leading to exceptional outcomes.

Deep Learning-Based Classification

Deep learning is a method for making predictions, classes, and clusters employing a NN that has been trained on massive quantities of data. The properties that DL architectures learn are constructed layer by layer [8]. For instance, a convolutional network's first layers are often where it learns patterns, textures, edges, and brightness from pictures. It may be reused since these picture attributes are utilized to analyze a wide variety of natural image types.

Convolutional Neural Networks (CNNs)

CNNs are a kind of deep feed-forward ANN that have found useful applications in visual picture analysis within the field of ML. CNNs employ a preprocessing-light variant of multilayer perceptrons. To determine the discrepancy among the forecasted and actual outputs, CNN modifies the backpropagation learning process. Then, using Gradient Descent, the network discovers the local best solution for adjusting the layer weights [9]. A CNN has several hidden layers in addition to an input and output layer. The hidden layers might be completely linked, pooling, or convolutional. The CNN architecture that we presented in this study consists of five layers: two convolutional layers, one pooling layer, and one fully linked layer.

Challenges and limitations

The following significant obstacles have been recognized after reviewing many publications and reviews:

The time required for manual labeling is greater. An extensive quantity of labeled training data is required for neural network training. It is computationally expensive to train on large datasets, even on powerful GPUs [10].

- ML and DL models are susceptible to training-related mistakes brought about by random features.
- Due to their flaw in understanding more relevant and complex data, traditional ML methods usually show fast convergence but low accuracy.
- The massive amount of features that deep learning algorithms must master causes them to be slow, yet they are typically correct.
- There is a severe lack of easily available reliable brain imaging datasets. Furthermore, the publicly accessible private data is noisy and does not adhere to normal formatting norms.
- Preprocessing is necessary to remove any noise and improve the suitability of the data. Nevertheless, a lot of people utilize subpar software that reduces rather than increases picture resolution.
- CNNs have the challenge of gathering a large amount of training data for the running process.

Current Trends in Brain Tumor Detection and Classification

Modern advancements in AI, particularly DL, have significantly influenced the creation of automated systems for detecting and classifying brain tumors. The current research tendencies are going more towards architectures that are more accurate, interpretable, computationally efficient, and clinically relevant to the real world. The goals of these trends include dealing with the variability of data, non-explanability, and the necessity to be deployed in various healthcare settings. The subsequent subsections point out the most striking current research directions that influence the field.

Deep Learning and Transfer Learning-Based Approaches

A ability of CNNs and other DLmodels to automatically acquire high-level picture information has made them indispensable in the study of brain cancers [11]. Since it allows pre-trained models such as EfficientNetB7, ResNet, and MobileNet to be optimized on medical data and to be generally extremely accurate with minimal training data, transfer learning has gained popularity. The strategy solves the problem of the lack of annotated medical images, as well as enhancing the efficiency of learning.

Explainable Artificial Intelligence (XAI)

The concept of explainability is one of the emerging trends that intend to make predictions more understandable to clinicians. Grad-CAM, attention heatmaps, and saliency maps are just some of the methods used to indicate the areas that have an effect on which the model makes a decision, thus improving trust and helping radiologists interpret the results of the diagnostic process. XAI is particularly significant in terms of acceptance by regulations and clinical practice integration.

Vision Transformers and Attention-Based Models

Attention-based and Vision Transformers (ViT) are becoming increasingly popular because they are able to capture longer-range spatial relationships as compared to traditional CNNs. These models determine the relationship between regions of the brain worldwide, enhancing the recognition of tumor boundaries, as well as subtypes. ViT has demonstrated good achievements on MRI data, suggesting the transition into transformer-based medical imaging analysis.

Federated Learning and Privacy-Preserving AI

The transfer of medical images among hospitals is not easy with regard to privacy laws. Through Federated Learning, AI models can be trained collaboratively without sharing patient data, giving local institutions a chance to share their knowledge

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whilst keeping patient data local [12].. It is more generalizable to model and simultaneously ensures data confidentiality, which is suitable in the use of a multi-center clinical application.

Future Directions

Multi-class brain tumor detection and classification is a rapidly developing field, but there are several directions that are instrumental in moving the research to clinical implementation [13]. Developing larger and more varied multi-center MRI datasets is an important first step in making models more resilient and applicable to a wider range of patient populations. Also, the combination of multimodal data - e.g., MRI with genomic, clinical, or histopathological information - could yield more detailed and individualized diagnostic data. The other priority is the emergence of explainable AI (XAI) models to increase transparency and trust so clinicians could learn how diagnostic choices are achieved instead of trusting black-box predictions[14]. Lightweight and energy-efficient models, including MobileNet, will remain significant in real-time applications in resource-constrained environments, whereas high-performance models such as EfficientNetB7 can be customized to run on the hybrid cloud-edge systems to achieve accuracy and computational needs [15]. It is eventually a matter of clinical validation, regulatory clearance and implementation in the radiological process that allows safe and efficient use of AI-driven systems of tumor classification in the real healthcare environment.

Key Future Directions

- The creation of extensive datasets involving several institutions For better model generalizability across various imaging facilities and patient populations.
- Integration of Multimodal Data Combining MRI with clinical, genomic, and pathological data for more accurate diagnosis
- Explainable and Trustworthy AI Models (XAI) enhancing interpretability through visualization techniques such as Grad-CAM and attention maps.
- Lightweight Models for Real-Time Deployment
  Utilizing models like Mobile Net for on-device processing in low-resource clinical environments.
- High-Accuracy Scalable Architectures Optimizing models like EfficientNetB7 for high-resolution MRI classification tasks.
- Edge-Cloud Hybrid Diagnostic System Tradeoffs between local inference and cloud computing to scale healthcare AI.

Literature Review

- This section contains a list of the related research on AI-based methods of medical image analysis and how they could be used to enhance tumor identification and classification and clinical decision-making. The works suggest the innovations in the interpretability of the model, processes of attention, and segmentation, which makes the diagnostic results more dependable and effective.
- shaq et al., (2025) Grad-CAM is used to increase model interpretability and make it more explainable. After the input MRI images are enhanced with data, they go on to the feature extraction step, where the patterns of the tumor are learnt. The model's capacity to zero in on pertinent tumor locations is further shown by the XAI study, which improves the model's interpretability. This approach for brain tumor categorization is both accurate and easy to understand, which might greatly improve neuro-oncology clinical decision-making[16].
- Memon et al., (2025) used MobileNet as the pretrained network for the feature extraction process and convolutional block attention model for the visualization. Current study trained four models MobileNet CBAM, MobileNet SE, MobileNet ECA, MobileNet. Gliomas, meningiomas, no tumors, and pituitary were the four classes used to train the model using the Figshare dataset. Brain tumors are very deadly disease. The first step to investigating brain tumors is CT scan or MRI. The MRI images are then referenced for further investigation. It is very important to locate the tumors effectively. The manual methods of observing tumor location and shape can lead to wrong treatmen [17].
- Kotte and Ahmad, (2024) performanced evaluations to guide an iterative development process, the model's robustness and generalizability are strengthened, thereby increasing its potential for efficacy in a wide range of clinical scenarios. The use of this comprehensive technique is expected to lead to advancements in the categorization of brain tumors, which would in turn improve clinical decision-making [18].
- Agha et al. (2024) appeared in various scholarly journals, and this gives new scholars a solid ground to start with when conducting their respective literature reviews and learning the advantages and disadvantages of different ML algorithms in MRI brain tumor classification. Moreover, they know the effectiveness of every approach which enables them to avoid the problem-related steps and go directly to the root[19].
- Verma, Kaswan and Kumar Bharti, (2024) intended is to possibly alter clinical practice and to improve patient outcomes. The specific task of segmenting tumors in the MRI brain images is a very active sphere in the field of medics since MRI is a noninvasive method of imaging. Segmentation of the tumor may be used to separate the aberrant tissue of the brain and the normal brain tissue. The paper explores the numerous ML algorithms that are employed in classifying anomalies in MRI data and segmenting brain tumors. It provides a critical overview of these approaches[20].
- Soomro et al., (2023) examined the major segmentation techniques used in each study. The article provides an in-depth overview of the topic and illuminates the recent developments of the numerous ML and image segmentation procedures

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that are applied to the detection of brain tumors. A comparison between the DL approaches and state-of-the-art approaches reveals that they are superior to them in tumor segmentation of the brain MRI scans[21].

- Table II provides a summary of MRI-based AI tumor detection and classification experiments conducted recently. It summarizes the methodology in each of the studies, the main discoveries and limitations, noting the explanation of explainable DL models, the use of attention in feature extraction, and segmentation methods. Altogether, the articles indicate remarkable advances in the model accuracy and interpretability alongside overcoming the issues of data diversity and clinical application.

TABLE I. COMPARATIVE ANALYSIS OF AI-BASED APPROACHES FOR BRAIN TUMOR DETECTION AND CLASSIFICATION USING MRI

TABLE II.

Reference	Study On	Approach	Key Findings	Challenges / Limitations	Future Directions
Shaq et al., (2025)	Explainable deep learning for brain tumor classification	Incorporated Grad-CAM for explainability; MRI data augmentation; deep CNN for feature extraction	Grad-CAM improved model interpretability, focusing on relevant tumor regions; accurate classification aiding neuro-oncology decision-making	Limited generalization to unseen datasets; may require larger annotated datasets for clinical validation	Enhance real-world validation using multicenter datasets and integrate explainability into clinical workflow
Memon et al., (2025)	Brain tumor classification using MobileNet variants	Used MobileNet as pretrained network; added attention modules (CBAM, SE, ECA); trained on Figshare dataset (glioma, meningioma, no tumor, pituitary)	MobileNet CBAM achieved better visualization and accuracy; attention improved feature extraction	Limited dataset diversity; overfitting risk; dependency on pretrained weights	Apply to larger, multi-modal datasets; explore hybrid attention mechanisms; optimize for real-time clinical use
Kotte and Ahmad, (2024)	Model evaluation and robustness for brain tumor classification	Iterative performance evaluation approach to strengthen model generalizability	Enhanced model robustness and efficacy for broad clinical scenarios	May lack detailed explainability; dependent on dataset variety	Integrate XAI and transfer learning to improve interpretability and adaptability
Agha et al., (2024)	Literature review of ML techniques for MRI-based brain tumor classification	Comparative study of multiple ML algorithms and their pros/cons	Helps new researchers understand algorithmic strengths, weaknesses, and accuracy benchmarks	Review-based study; lacks empirical validation or implementation	Develop hybrid ML-DL frameworks targeting existing algorithmic gaps
Verma, Kaswan & Kumar Bharti, (2024)	MRI-based tumor segmentation and anomaly classification	Systematic review of segmentation techniques and ML models for tumor detection	Highlights MRI's role as a noninvasive technique and summarizes segmentation progress	Does not provide experimental results; challenges in integrating multi-source data	Focus on automated segmentation pipelines and real-time clinical integration
Soomro et al., (2023)	Comparative analysis of segmentation algorithms for brain tumor detection	Compared state-of-the-art ML and DL segmentation methods	Found that deep learning outperforms traditional ML in tumor segmentation	Computational complexity; large data requirements; interpretability issues	Explore lightweight DL models and explainable segmentation for clinical applicability

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Conclusion And Future Work

Automated procedures have significant opportunities of enhancing diagnosis and reduce the workload of radiologists in diagnosing and classifying multi-class brain tumors. DL approaches, particularly CNNs, have revolutionized the process of tumor classification by learning complex hierarchical patterns of MRI and other medical imaging modalities by itself, whereas traditional ML classifiers such as SVM, KNN, and RF have provided effective albeit more limited feature extraction functions. The results of classification are now stronger and more comprehensible as they have adopted the use of modern techniques such as transfer learning, attention models and ViTs. In spite of these developments, there are still issues of data deficiency, model explicability, computational expense, and generalizability across various clinical settings.

Future studies ought to aim at creating large multi-institutional, and multi-modal datasets to make the models more robust and adaptable in diverse population groups of patients. The explainable AI (XAI) methods will still have to develop so that transparency and confidence in clinicians in automated decision-making systems are achievable. Besides, light and energy-efficient deep learning models, like MobileNet and EfficientNet implementations, ought to be trained to operate in real-time and to be deployed over the edge, to resource-constrained healthcare settings. The incorporation of federated learning will be essential in preserving patient privacy and facilitating joint training among several hospitals.

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