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An Overview of Current Developments in Artificial Intelligence for Brain Tumor Diagnosis

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ABSTRACT: Medical diagnostics has undergone a revolution thanks to artificial intelligence particularly in the classification and identification of brain tumors. Developments in deep learning and machine learning have enabled the examination of medical imaging data, such as magnetic resonance imaging and computed tomography, automatically, accurately, and efficiently. Early diagnosis and individualized treatment planning are facilitated by AI-driven models, especially convolutional neural networks, which have shown exceptional performance in tumor segmentation, classification, and prognosis prediction. Notwithstanding these developments, obstacles to broad clinical application include data accessibility, model interpretability, and clinical validation. This review highlights current trends, difficulties, and potential avenues for future research as it examines recent advancements in AI applications for brain tumor diagnosis. The focus is on integrating AI technologies into practical healthcare workflows, increasing explainability, and improving the generalizability of AI models. The results indicate that AI may be able to greatly enhance the detection of brain tumors, but further study is required to overcome current constraints and guarantee its safe, moral, and efficient application in healthcare.

KEYWORDS: Computed Tomography, Deep Learning, Medical Imaging Analysis, Neural Networks, Pattern Recognition, Radiomics.

I. INTRODUCTION

One of the most complicated and potentially fatal neurological conditions, The diagnosis, prognosis, and treatment planning of brain tumors are fraught with challenges. Improving patient outcomes requires the early and accurate identification of brain cancers, however, conventional diagnostic techniques including magnetic resonance imaging and computed tomography scans often rely on radiologists' subjective interpretation, which could result in inconsistent diagnoses.

Artificial intelligence has been a game-changing technology in medical imaging and diagnostics in recent years, providing automated, precise and efficient approaches for identifying and classifying brain tumors. Large-scale neuroimaging data analysis has shown impressive potential using AI-powered methods, particularly deep learning and machine learning, which facilitate tumor segmentation, grading, and treatment response prediction.

The current developments in AI applications for brain tumor diagnosis are examined in this review, which also highlights important approaches, difficulties, and potential future prospects. This study attempts to shed light on how AI is developing to improve patient care and diagnostic precision in neuro-oncology by investigating its integration with radiological imaging and clinical decision-making.

II. LITERATURE SURVEY

(Saeedi, Rezayi, Keshavarz, & R. Niakan Kalhori, 2023) A dataset of 3,264 MRI images was preprocessed and augmented before being analyzed using a newly developed 2D Convolutional Neural Network and a convolutional autoencoder network. The 2D CNN, consisting of multiple convolutional and pooling layers with batch normalization, achieved a training accuracy of 96.47%, while the auto-encoder network reached 95.63%. Their area under the ROC curve was almost 1, and their average recall values were 95% and 94%, respectively. Six machine learning models were also evaluated; The findings showed that K-Nearest Neighbors performed the best at 86% accuracy, while Multilayer Perceptrons had the lowest accuracy at 28%. According to statistical analysis, deep learning models performed noticeably better than conventional machine learning techniques with p-value < 0.05.





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(Amjad Rehman et al., 2021) This work suggests a deep learning-based technique for classifying and detecting tiny brain tumors. Prior to being processed by a pretrained CNN for feature extraction, tumor areas are initially extracted using a 3D Convolutional Neural Network. For final classification, a feed-forward neural network is used to evaluate the most pertinent characteristics, which are chosen using a correlation-based algorithm. Three BraTS datasets 2015, 2017, and 2018 were used to evaluate the model, and it demonstrated good accuracy with 98.32%, 96.97%, and 92.67%, respectively. The suggested approach offers competitive accuracy for brain tumor identification and classification when compared to current methods.

(Maqsood, Damaševičius, & Maskeliūnas, 2022) This paper presents a precise method for identifying and categorizing brain tumors. Five steps make up the suggested method: (1) enhancing image edges with linear contrast stretching; (2) Using a bespoke 17-layer deep neural network to segment cancers; (3) extracting features utilizing a MobileNetV2 modification with transfer learning; and (4) Choosing features with a multiclass support vector machine and an entropy-based controlled approach, and (5) M-SVM classification of pituitary tumors, gliomas, and meningiomas. Figshare and BraTS 2018 datasets were used to test the approach, and the results showed high accuracy of 98.92% and 97.47%, respectively. Its superiority over current methods in both visual and quantitative evaluations is confirmed by experimental data.

(Majib, Rahman, Sazzad, Khan, & Dey, 2021) Brain tumors, which have a constantly rising death rate, are potentially fatal disorders brought on by the uncontrolled growth of brain or skull cells. Effective treatment and increased patient survival rates depend on the early diagnosis of malignant tumors. However, manually diagnosing and segmenting tumors from MRI scans takes a lot of time and is mostly dependent on the skill of radiologists. This work investigates several conventional and hybrid machine learning (ML) models for brain tumor classification in order to address these issues. To find the best neural network-based categorization method, 16 distinct transfer learning models were also assessed. VGG-SCNet (VGG Stacked Classifier Network), a stacked classifier, was created and performed better than any other model. The proposed model showed 99.2% precision, 99.1% recall, and 99.2% F1-score for automated brain tumor identification, demonstrating its exceptional efficacy and accuracy.

(Kumar, Kakarla, Isunuri, & Singh, 2021) To address these issues, this paper suggests a deep learning model that combines global average pooling and ResNet-50. A dataset of 3,064 MRI pictures with three different kinds of the model was tested on brain malignancies. The suggested model was compared to other competitive models using performance criteria. The suggested model outperformed current models in classification accuracy, achieving Accuracy with data augmentation: 97.08% and 97.48% accuracy without data augmentation.

(Khairandish, Sharma, Jain, Chatterjee, & Jhanjhi, 2022)The proposed approach integrates CNN for feature extraction, SVM for categorization and a threshold-based segmentation method for identifying tumors. The model was evaluated against existing techniques, where it outperformed them with an accuracy of 98.50%, surpassing techniques like CNN alone 97.5%, k-NN 96.6%, Deep CNN with Discrete Wavelet Autoencoder 96%, Rough Extreme Learning Machine 94.23%, and Deep CNN 95%. The study highlights the challenges of brain tumor detection due to variations in cell growth, shape, and location. MRI remains the standard imaging method, but traditional machine learning approaches often depend on handcrafted features, leading to potential in accuracies. **Table 1** showing the different techniques and dataset used in previous research work.

Table 1. Different techniques given different accuracy for previous research work

Sr No	Paper Title	Dataset	Accuracy (%)	Techniques Used
1	(Amin, Sharif, Raza,	BRATS 2012, 2013,	90, 89,	3D CNN + RF, U-net based Fully
	& Yasmin, 2024)	2014, 2015, ISLES 2015	94, 91	Convolutional Networks
2	(Iqbal et al., 2019)	MICCAI	82.29	ConvNet and LSTM
		BRATS 2015		
3	(Arshia Rehman, Naz,	MRI slices of brain	98.69	AlexNet, GoogLeNet, and
	Razzak, Akram, &	tumor dataset Figshare		VGGNet
	Imran, 2020)	_		





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4	(Sharif et al., 2020)	BRATS 2012, 2013, 2014 and 2015	0.99, 0.98 0.98, 96.5	ELM and RELM-LOO machine learning classifiers.
5	(Bhanothu, Kamalakannan, & Rajamanickam, 2020)	MRI Images	77.60	Faster R-CNN
6	(Agarwal, Jain, Gupta, Sawhney, & Mittal, 2023)	MRI images	97.3	CNN
7	(Khan et al., 2022)	MRI images	92.13	Hierarchical Deep Learning-Based Brain Tumor (HDL2BT)
8	(Qureshi et al., 2022)	T1-weighted CE-MRI dataset 2D-scanned MRI slices	97.30	Ultra-Light Deep Learning Architecture (UL-DLA)
9	(Ullah et al., 2022)	MRI dataset	98.91%	Mobilnetv2+Densenet201+ Squeeznet+Alexnet+Googlenet+ Inceptionv3+Resnet50+Resnet18+ Resnet101+Xception+ Inceptionresnetv3+VGG19+ Shufflenet are the hybrid DL techniques that were employed in the tests.
10	(Arbane, Benlamri, Brik, & Djerioui, 2021)	MRI images	98.42	ResNet, Xception and MobilNet- V2

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1. Key Contribution by Previous Research Work

Key contribution by previous research work showing in Table 2.

Table 2.	Research	contributions	in	previous	articles
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Sr No	Paper Title	Key Contribution
1	(Amin et al., 2024)	An automated method for early glioma and ischemic stroke identification and categorization is presented in this publication. This publication presents an automated method for brain tumor segmentation and discrimination.
2	(Iqbal et al., 2019)	Long short-term memory and convolutional neural networks are used in this study's deep learning models to accurately identify brain tumors from reference medical photos. Sequence learning model proposal for patch-wise image segmentation.
3	(Arshia Rehman et al., 2020)	In order to categorize and automatically detect brain tumors, new and reliable transfer and deep learning algorithms are introduced. These techniques are successful in extracting significant and rich features from a benchmark Figshare dataset. To provide a thorough evaluation of the main elements influencing the pretrained models' fine-tuning strategy. Prior to sending the data to the support vector machine for classification, the multiple pretrained model freeze layers should be used.
4	(Sharif et al., 2020)	Fuzzy-based unsupervised clustering is employed for segmentation, The tumor region is refined using mathematical morphology, and the image is smoothed using triangular fuzzy median filtering.
5	(Bhanothu et al., 2020)	Brain tumors were automatically detected and categorized using the Faster R-CNN algorithm. Convolutional feature maps are created for tumor region classification and recommendation. The





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		VGG-16 architecture served as the fundamental network for Faster R-CNN.
6	(Agarwal et al., 2023)	We used a CNN-based classifier in our study that was collected from Kaggle and operates on the dataset's classification principle.
7	(Khan et al., 2022)	A novel machine learning (ML) methodology is presented in this article to get around this accurate brain tumor segmentation. Four classifications have been established for the suggested intelligent detection methodology for detecting brain tumors: pituitary, meningioma, glioma, and tumor.
8	(Qureshi et al., 2022)	This paper suggested a unique Ultra-Light Deep Learning Architecture (ULDLA) that uses SVM to predict MRI brain cancers by extracting deep features and textural data.
9	(Ullah et al., 2022)	Installing a DL-based system to automatically detect and classify brain malignancies into three categories: meningioma, pituitary, and glioma. We study and evaluate the TL concept for nine different deep neural networks. assessing how well and precisely each TL model can classify brain MRI images. Evaluating the effectiveness of hybrid techniques (DL + SVM) versus TL approaches.
10	(Arbane et al., 2021)	Brain MRI images are to be classified as either brain tumor-free or brain tumor-containing using the suggested transfer learning- based technique.
11	(Ayadi, Elhamzi, Charfi, & Atri, 2021)	An innovative and reliable approach that effectively extracts significant information from the MRI dataset is given for the automated categorization of brain cancers.
12	(Amjad Rehman et al., 2021)	To improve the diagnosis of brain tumors, present an improved model. It suggests an enhanced convolutional neural network based brain tumor classification model based on a sophisticated 3D model. The two submodules that make up the proposed Brain Tumor Classification Model are (i) a segmentation model and (ii) CNN hyperparameter optimization using an adaptive dynamic sine-cosine fitness grey wolf optimizer technique following the training model. The ADSCFGWO method utilizes the strengths of In a versatile framework, the sine cosine and grey wolf algorithms.
13	(Kader et al., 2021)	A variation advanced convolutional neural network model was proposed in this study to distinguish between healthy and pathological MR brain images. In differential CNN networks, feature maps were produced using a differential factor and pre- established hyperactivity values.
14	(Tiwari et al., 2022)	We proposed an automated technique in this study to use MRI to detect multiclass classification of brain tumors.
15	(Masood et al., 2021)	The suggested technique is capable of accurately segmenting and classifying brain tumors from MRI images even when the input pictures contain noise, blurring, and bias field-effect variations. The DenseNet-41-based Mask-RCNN's efficient region proposal network, which operates end-to-end, is responsible for the precise identification and segmentation of tumor regions.
16	(Raza et al., 2022)	We suggest a hybrid deep learning approach for three distinct BT categorization categories pituitary, meningiomas, and gliomas. The suggested DL classification method surpasses the state-of-the-art methods by exhibiting the greatest accuracy on the CE-MRI dataset after extensive testing with 9 distinct pre-trained deep learning models employing transfer learning techniques.





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17	(Saleh, Sukaik, & Abu-Naser, 2020)	This study examines the drawbacks resulting from MRI equipment' incapacity to detect and categorize cancers.
18	(Iqbal, Ghani, Saba, & Rehman, 2018)	A deep convolutional neural network for brain tumor segmentation in MRIs is presented in the proposed work. The proposed network uses the BRATS segmentation challenge dataset, which includes images captured with four different modalities.
19	(Sadad et al., 2021)	The Unet architecture, which uses ResNet50 as its backbone, is used to identify brain tumors. Data augmentation is a technique used to improve outcomes on small datasets. NASNet is a novel optimized framework that applies the concepts of Reinforcement Learning and Evolutionary Algorithms to the optimization job. Lastly, we used several deep transfer learning models for brain tumor classification, including ResNet50, DenseNet201, MobileNet V2, and InceptionV3. To demonstrate the effectiveness of the NASNet model, we contrasted them with it.

2. Image Size, Dataset, and Quantity of Images Used in Earlier Research

Summary for the different dataset, image size and number of images used in previous research work showing in **Table 3**.

Table 3. An overview of the various datasets, image sizes, and quantity of images utilized

Paper Title	Dataset	Image Size	Number of Images
(Iqbal et al., 2019)	MICCAI BRATS 2015 brain cancer data	$155 \times 240 \times 240$	384
(Arshia Rehman et al., 2020)	publicly available brain tumor dataset—Figshare	512 × 512	3064
(Bhanothu et al., 2020)	MR images	512 × 512	2406
(Khan et al., 2022)	Publicly available brain tumor dataset—Kaggle Dataset	512 × 512	3264
(Qureshi et al., 2022)	CE-MRI dataset	224×224	3064
(Ullah et al., 2022)	(MRI) dataset Kaggle Dataset	224 × 224	3064
(Arbane et al., 2021)	MRI images	224×224×3	1516
(Ayadi et al., 2021)	MRI brain tumor	256×256	3064
(Agarwal et al., 2023)	MRI	512 × 512	3064
(Kader et al., 2021)	MR brain images	256 × 256	1400
(Tiwari et al., 2022)	Brain Tumor Classi0cation (MRI) from the Kaggle licensed CCO: Public Domain	224 × 224 × 3	3264
(Masood et al., 2021)	MRI datasets	512 × 512	3264
(Raza et al., 2022)	CE-MRI dataset Nanfang Hospital Guangzhou China and General Hospital Tianjin	512 × 512	3062





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	Medical		
	University		
	in China		
(Iabel et al. 2018 $)$	BRATS 2015	155 × 240 × 240	274
(iqual et al., 2018)	dataset	133 × 240 × 240	274
	slices of brain		
Sadad et al. 2021)	MRI taken from	512 × 512	3,064
(Sadad et al., 2021)	233 patients	512 ~ 512	
	(Cheng, 2017)		

III. CONCLUSION AND FUTURE WORK

By improving the precision, effectiveness, and automation of medical imaging analysis, artificial intelligence (AI) has drastically altered the brain tumor diagnosis. In tumor identification, segmentation, and classification, machine learning and Among deep learning models, convolutional neural networks have shown impressive performance. Additionally, AI-driven methods have enhanced prognosis prediction, tailored therapy planning, and early diagnosis, all of which have contributed to better patient outcomes. Widespread use is still hampered by issues including clinical validation, model interpretability, and data paucity. Even though AI has a lot of potential, further development is required to close the gap between research and practical clinical applications. Future studies should concentrate on enhancing the robustness and generalizability of AI models by combining various, excellent datasets from various organizations. For AI-driven choices to be trusted by medical professionals, explainability and openness must be given top priority. Furthermore, improving diagnostic accuracy can be achieved by combining AI with multimodal data, including genetic, histological, and clinical information. It is important to investigate the creation of real-time AI-assisted diagnostic tools and how well they fit into clinical processes. Lastly, to guarantee the safe and efficient application of AI in brain tumor diagnostics, ethical issues and regulatory permission must be taken into account.

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