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A Comprehensive Survey on Machine Learning and Deep Learning based Robust Brain Tumor Detection

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ABSTRACT

Brain tumors, whether benign or malignant, pose significant diagnostic and therapeutic challenges due to their complex nature, critical brain location, and high mortality rates. Early detection is often hindered by nonspecific symptoms and the limitations of manual MRI interpretation, which is time-consuming and prone to errors. Recent advancements in artificial intelligence (AI) and deep learning have shown promise in improving brain tumor diagnosis, segmentation, and classification. Techniques such as U-Net, VGG-19, Deep Tumor, and differential CNN architectures have achieved remarkable accuracy, enhancing tumor boundary detection essential for surgical planning and treatment optimization. However, issues like limited annotated datasets, lack of generalizability, and the “black-box” nature of AI remain barriers to clinical adoption. This study surveys state-of-the-art methodologies, identifies key challenges in brain tumor detection and treatment, and highlights potential solutions, including AI- assisted imaging, targeted therapies, and accessible diagnostic platforms, aiming to improve survival rates and the quality of life for brain tumor patients.

Index Term: *Brain Tumor Detection, Deep Learning, MRI Segmentation, U-Net, Convolution Neural Networks (CNN) etc.*

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I. INTRODUCTION

A brain tumor is an abnormal growth of cells inside the brain or skull; some are benign, others malignant [1]. Tumors can grow from the brain tissue itself (primary), or cancer from elsewhere in the body can spread to the brain (metastasis). Treatment options vary depending on the tumor type, size and location [2]. Treatment goals may be curative or focus on relieving symptoms. Many of the 120 types of brain tumors can be successfully treated. New therapies are improving the life span and quality of life for many people [3].

During the process of normal cell growth, new cells replace injured or old cells in a way that is under control. Tumor cells multiply in an uncontrollable manner for reasons that are not completely understood [4]. An abnormal growth that begins in the brain and does not often spread to other regions of the body is referred to as a primary brain tumor [2] [6]. There are two types of primary brain tumors: benign and malignant. Benign brain tumors are characterized by their moderate growth, defined borders, and minimal likelihood of spreading. Benign tumors, despite the fact that their cells are not cancerous, might pose a danger to one's life if they are situated in an area that is crucial [5]. A malignant brain tumor is characterized by rapid growth, uneven borders, and the ability to spread to neighboring regions of the brain. Malignant brain tumors do not meet the criteria for the classification of cancer since they do not spread to organs other than the brain and spine, despite the fact that they are often referred to as brain cancer. Brain tumors that are metastatic, also known as secondary brain tumors, originate in another part of the body and then spread to the brain [1] [7].

Cancer cells that are transported via the bloodstream may give rise to these tumors. Breast and lung cancer are the two types of cancer that spread to the brain the most often. It does not matter if a brain tumor is benign, aggressive, or metastatic; all of these types of tumors have the potential to be fatal [6]. As a result of being contained inside the bony skull, the brain is unable to expand in order to accommodate a rising mass. As a consequence of this, the tumor causes normal brain tissue to be compressed and displaced. A blockage of cerebrospinal fluid (CSF), which is fluid that circulates around and through the brain, may be caused by some types of brain tumors [9]. This obstruction causes an increase in intracranial pressure, which may lead to hydrocephalus, which is an enlargement of the ventricles. Edema is a symptom that is caused by some brain tumors. The "mass effect," which is caused by factors such as size, pressure, and edema, is responsible for many of the symptoms (Fig. 1) [10].

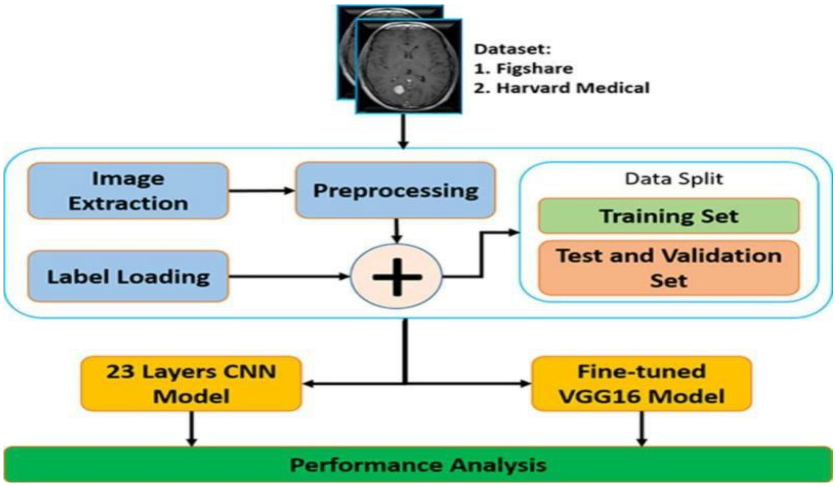

Figure 1. : Brain tumors detection via deep learning [1]

A. ***Magnetic Resonance Imaging (MRI)***:- **MRI** has become essential in the non-invasive diagnosis of brain tumors, providing intricate images of the brain's structure and abnormalities. The MRI offers exceptional soft tissue contrast, enabling the differentiation between healthy and diseased tissues. This is essential for evaluating the tumor's position, dimensions, and possible effects on nearby brain structures, which is vital for devising a treatment strategy. Nonetheless, the analysis of MRI scans heavily depends on the proficiency of radiologists and can be a lengthy process, underscoring the necessity for supportive technologies to enhance diagnostic precision and effectiveness [11].

B. ***CT Scan:-*** Brain tumor detection using CT (Computed Tomography) scans involves analyzing cross- sectional images of the brain to identify abnormal growths. CT scans are widely used in emergency settings due to their speed and effectiveness in detecting hemorrhages, swelling, and certain types of tumors. Tumors in CT scans may appear as either dark (hypo dense) or bright (hyper dense) areas depending on their type and whether contrast material is used. Automated brain tumor detection using artificial intelligence typically follows a structured pipeline. It begins with data collection from sources such as The Cancer Imaging Archive (TCIA), Fig share, or hospital records. Preprocessing steps are essential and may include resizing images, normalizing pixel values, converting DICOM images to common formats like PNG or JPEG, applying contrast enhancement, and optionally performing skull stripping to isolate brain tissue. Deep learning models, especially Convolutional Neural Networks (CNNs) such as ResNet, VGG, Mobile Net, or Efficient Net, are commonly used for classification tasks, while architectures like U-Net, SegNet, or Mask R-CNN are preferred for segmentation, which involves identifying the exact location of tumors within the image.

TABLE 1: Comparison of different Imaging Technology for MRI Detection

Modality	Primary Use	File Format	AI Suitability
MRI CT	Structural and functional brain imaging Quick	.dcm, .nii	Excellent Good
PET	structural imaging, emergency	.dcm, .png	Useful
	Metabolic tumor activity	.dcm, .nii	

Modality	Primary Use	File Format	AI Suitability
SPECT	Perfusion/metabolic data	.dcm	Limited
X-ray	Rare for brain tumors	.dcm, .jpeg	Not ideal
Ultrasound	Neonatal & surgical support	.dcm, .jpeg	Niche use

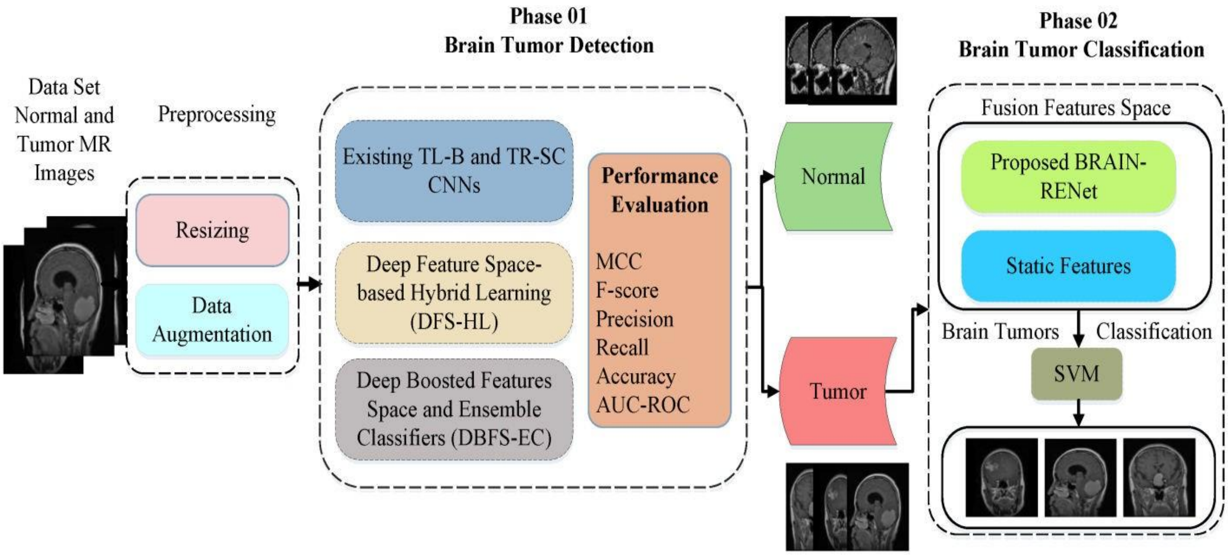

Figure 2. : Stages of classification of the brain tumor detection [5]

In the next section II discuss the literature survey of different previous techniques which is used in the last decade. In the last decade there are different previous methods presented in the last decade. Section III discuss the problem formulation of the research work. Further discuss the expected solution in section IV, conclusion & future work are discuss the in section V.

II. LITERATURE SURVEY

In the previous section discuss about the introduction of the brain tumor detection. In the next section II discuss the literature survey of different previous techniques which is used in the last decade.

Mohsen Asghari Ilani et.al (2025) Beseechers examine the efficiency of convolutional neural networks like Inception-V3, EfficientNetB4, and VGG19, enhanced by transfer learning. Assessment criteria including F- score, recall, precision, and accuracy were used to evaluate model performance. U-Net segmentation design excelled with 98.56% accuracy, 99% F-score, 99.8% area under the curve, and 99% recall and precision rates. This research shows that U-Net, a convolutional neural network design, effectively segments brain tumors for early identification and treatment planning. With an accuracy of 96.01% in cross-dataset validation with an external cohort, U-Net demonstrated strong performance in many clinical settings. Our research suggests that U-Net and transfer learning may improve diagnostic accuracy, clinical decision-making, and patient care, eventually increasing outcomes in neuroimaging [1].

Muhammad Faheem Khan et.al (2024) This work introduces the OT model, a computer-aided technique for precise brain glioma detection. The approach started with MRI data gathering from glioma patients and healthy controls at Bahawal Victoria Hospital (BVH-RDL). Image quality was improved by preprocessing techniques such as histogram equalization, grey-level collection, noise reduction, and tumor identification using expert radiological input. These preprocessing steps enabled accurate feature extraction and analysis of MRI images. The model used GLCM for texture analysis and a feature selection scheme that included Fr, POE, AC, and MI to identify the top 30 most relevant features. These characteristics were examined by three machine learning classifiers. While the CNN classifier had a slightly better accuracy of 84.50%, the LSTM classifier obtained 83.71% accuracy. The findings show that the OT model may improve gloom detection and achieve high accuracy in practical applications [2].

Monika Agarwal et.al (2024) The classifier uses a two-phase strategy to complete its work. In the first phase, ODTWCHE improves picture contrast for accurate brain tumor diagnosis. In the next step, the classifier uses deep transfer learning and the pre-trained Inception V3 model to enhance the diagnostic process. tumor categorization. The proposed system outperformed state-of-the-art models like Alex Net, VGG-16, DenseNet-201, VGG-19, GoogLeNet, and ResNet-50 with the highest accuracy of 98.89% on MRI images with varying contrast and brightness levels. The resilience of the system is shown by its accurate identification and categorization of colorful datasets. The article discusses the use of metrics in several areas, including academia, and potential issues arising from wrong implementation. They stress the need of aligning measures with system goals and minimizing negative consequences that might distort data or enable manipulation of incentives. The authors provide a comprehensive approach for developing measurements, including design, remedies for negative consequences, and essential needs [3].

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Amena Mahmoud et.al (2023) Machine learning, especially deep learning, is becoming crucial for classifying massive datasets, particularly in medical fields. These strategies enhance human capacity to handle huge datasets by identifying key qualities. This research examines the significance of CNN models (VGG-16, VGG-19, and Inception-V3) on a brain tumor dataset using several metrics. We examined the accuracy, sensitivity, and specificity of the used models. Classifier accuracy was 97.2%–98.95%. The VGG-19 model with AQO optimizer resulted in the best accuracy and better results compared to other models [4].

Ghazanfar Latif et.al (2022). Brain tumors are painful and dangerous. If not detected early, it may result in death. Manual tumor segment excision by physicians is time-consuming and irreversible. This research introduces DeepTumor, a paradigm for classifying glioma tumors into four classes: edema, necrosis, enhancing, and non-enhancing. The suggested multistage automated brain tumor categorization approach is very accurate and may help radiologists diagnose brain tumors early. Experiments used multimodal (Flair, T1, T1c, T2) BraTS 2015 MRI dataset. In the first stage, CNN classifier model 2 obtained 98.74% accuracy for HGG and 97.33% accuracy for LGG MR Image classification. The second step included segmenting the tumorous area of the picture using a new approach that combines Fuzzy C-means (FCM) information from nearby images with the actual image. This method improved the accuracy of tumor region information extraction. The third stage grouped segmented glioma tumors into four classes: necrosis, edema, non-enhancing, and enhancing. Deep CNN Classifier attained an average accuracy of 96.30% for multiclass tumor classification in experiments [5].

Khusboo muniret.et.al (2022) This research aims to suggest a strategy for detecting brain cancers. Segmentation methods in Magnetic Resonance (MR) pictures identify brain malignancies. Recent research suggests that deep learning may extract particular characteristics of brain tumors in radiographic pictures, helping clinical diagnosis. To create automated screening techniques, most data scientists and AI researchers focus on Machine Learning methodologies. Automated segmentation yields faster results and more reliable brain tumor diagnosis, despite potential variances in data sources and recording processes. This study proposes and tests various designs to enhance segmentation performance. Our proposal involves training deep neural networks using patient MRI data to identify brain malignancies. The suggested brain tumor segmentation architectures use convolutional neural networks and inception modules. Comparing these suggested designs to the basic reference ones yields intriguing findings. Compared to baseline Unet design, MI-Unet improved dice score by 7.5%, insensitivity by 23.91 %, and specificity by 7.09%.The depth-wise separable MI-Unet design improved dice score by 10.83%, sensitivity by 2.97%, and specificity by 12.72% compared to the baseline Unet architecture. Hybrid Unet design improved dice score by 9.71%, sensitivity by 3.56%, and specificity by 12.6%. Although the depth-wise separable hybrid The Unet architecture exceeded the baseline by 15.45% in dice score, 20.56% in sensitivity, and 12.22% in specificity [6].

Andronicus A. Akinyelu.et.al (2022) This article presents a detailed review of advanced deep learning models used for brain tumor classification and segmentation, focusing on CNN-, CapsNet-, and Vision Transformer (ViT)-based architectures. While CNNs have shown strong performance, they struggle with issues like data imbalance, rotation variance, and limited multi-task functionality. CapsNet offers improved accuracy with fewer parameters and better robustness to spatial changes, while ViTs and Swin Transformers are emerging as powerful alternatives for image analysis. The study emphasizes the need for frameworks that integrate segmentation, classification (benign/malignant), and grading. Future directions include the adoption of 3D CNNs, uncertainty modeling (e.g., Bayesian CapsNet), novel activation functions (e.g., PSTanh), and high-resolution feature retention.

Additionally, integrating multi-modal imaging, autoencoders, and data augmentation via GANs can enhance diagnostic accuracy. Reported models like CapsNet achieved high performance (e.g., >98% accuracy) on small datasets, indicating strong potential for future development in medical imaging applications [7].

Isselmou Abd El Kaderet.al (2021) deep learning algorithms have advanced significantly in medical image processing and analysis. Using magnetic resonance imaging to categorize brain cancers is challenging owing to the complex brain structure and interconnected tissues, as well as the great density of the brain. Our approach uses a deep convolutional neural network (CNN) to identify brain tumors, including aberrant and normal MR images. We produced new differential feature maps in the original CNN feature maps using differential operators in the deep- CNN architecture. The derivation method improved the performance of the suggested strategy based on evaluation parameters. The differential deep-CNN model excels at analyzing pixel directional patterns utilizing contrast calculations, allowing for accurate classification of vast databases without technological issues. The suggested technique performs well overall. We tested and trained our model using 25,000 brain MRI scans, including aberrant and normal pictures. The experimental findings indicated a 99.25% accuracy for the suggested model. This work supports the adoption of a differential deep-CNN model for automated brain tumor categorization [8].

Muhammad Attique Khan.et.al (2020) Identifying brain tumors manually is error-prone and time-consuming for radiologists, making an automated solution essential. Binary classification, such malignant or benign, is simple, however radiologists have challenges in classifying multimodal brain tumors (T1, T2, T1CE, and Flair). We provide a deep learning-based automated multimodal classification technique for brain tumor types. The suggested approach has five key phases. Step one involves employing edge-based histogram equalization and discrete cosine transform (DCT) to apply linear contrast stretching. The second part involves deep learning feature extraction. Two pre-trained CNN models, VGG16 and VGG19, were employed for feature extraction via transfer learning. In the third stage, a correntropy-based joint learning technique and extreme learning machine (ELM) were used to identify the best features. The fourth phase was combining robust covariant features using partial least square (PLS) methods into a single matrix. The merged matrix was sent to ELM for categorization. The approach was verified using BraTS datasets, achieving 97.8%, 96.9%, and 92.5% accuracy for BraTs2015 [9].

Sidra Sajid1.et.al (2019) Gliomas are the most aggressive and deadly brain tumors that grow quickly. Using computer-aided diagnostics to segment gliomas is problematic owing to their uneven form and diffuse borders with the surrounding region. Magnetic resonance imaging (MRI) is the most used approach for visualizing brain structures. This paper presents a deep learning-based technique for brain tumor segmentation using several MRI modalities. The proposed hybrid convolutional neural network architecture considers local and contextual information, using a patch-based technique to predict output labels. In the proposed network, dropout regularizer and batch normalization address over-fitting, while two-phase training addresses data imbalance. The approach includes preprocessing for picture normalization and bias field correction, a CNN feed-forward pass, and post- processing for removing minor false positives surrounding the skull. The approach is verified using BRATS 2013 dataset, achieving better results than state-of-the-art methods in dice score, sensitivity, and specificity for the overall tumor area (0.86, 0.86, and 0.91) [10].

TABLE.II: Comparison of Different Methods

Ref. / Year	Approach / Model	Dataset	Tumor Types	Accuracy and Other result Parameter
[1]/2025	U-Net segmentation architecture	T1-weighted MRI	Brain tumors	Accuracy: 98.56%, F-score: 99%, AUC: 99.8%, Recall & Precision: 99%; Cross-dataset validation accuracy: 96.01%
[2]/2024	GLCM + Fr, POE, AC, MI + CNN/LSTM classifiers	MRI from BVH-RDL (custom)	Glioma	CNN: 84.50 LSTM: 83.71
[3]/2024	ODTWCHE + Inception V3	MRI images with varying contrast	Brain tumors	Accuracy: 98.89%
[4]/2023	VGG-19 with AQO optimizer	Brain tumor dataset	Brain tumors	Accuracy: 98.95%
[5]/2022	DeepTumor: Multi-stage CNN + Fuzzy C-means	BraTS 2015 MRI	Glioma (HGG, LGG), Edema, Necrosis, Enhancing, Non-enhancing	Stage 1: HGG Accuracy: 98.74%, LGG Accuracy: 97.33%; Stage 3: Multiclass Accuracy: 96.30%
[6]/2022	3D CNNs, Bayesian CapsNet, GANs, Autoencoders	Small MRI datasets	Multi-class Tumors	98% (on small datasets)
[7]/2022	MI-Unet, Hybrid Unet, Depth-wise separable Unet	MRI datasets	Brain tumors	Dice Score improvement: 15.45%; Sensitivity improvement: 20.56%; Specificity improvement: 12.22%
[8]/2021	Differential Deep CNN	25,000 MRI scans	Normal vs. Abnormal brain images	Accuracy: 99.25%
[9]/2020	VGG16, VGG19 + ELM + PLS + Correntropy-based joint learning	BraTS 2015, 2017, 2018	Malignant / Benign (Multimodal: T1, T2, T1CE, FLAIR)	97.8% (BraTS2015), 96.9% (2017), 92.5% (2018)
[10]/2019	Hybrid CNN (patch-based, with dropout & BN)	BraTS 2013	Gliomas (aggressive brain tumors)	Dice Score: 0.86, Sensitivity: 0.86, Specificity: 0.91

III. PROBLEM IDENTIFICATION

The identification and treatment of brain tumors pose considerable medical and technical hurdles, as shown in the examined literature. Early identification is challenging because to the overlap of symptoms such headaches, seizures, and memory loss with other neurological disorders, resulting in diagnostic delays until tumors progress to an advanced stage. Imaging modalities like as MRI and CT scans, although essential for determining tumor dimensions, classification, and localization, rely significantly on manual analysis by radiologists, a process that is labor-intensive and susceptible to human error. Distinguishing among tumor types, including gliomas, meningiomas, and metastatic cancers, is notably intricate without invasive biopsy techniques. Precise tumor categorization is essential for treatment planning; yet, misclassification may result in unsuitable therapy, elevating mortality and recurrence rates, particularly in high-grade gliomas. Surgical planning is jeopardized by inaccurate tumor border diagnosis, and some cancers are deemed inoperable owing to their important cerebral placement.

From a technical perspective, deep learning and AI-driven diagnostic systems show promising outcomes but encounter difficulties, including the need for extensive, annotated datasets, substantial computing demands, and inadequate generalizability across diverse clinical environments. The absence of interpretability in these AI models fosters doubt about their clinical implementation, since medical practitioners want clear and elucidative decision- making tools. Social and economic obstacles endure, including exorbitant treatment expenses, restricted access to sophisticated care in rural areas, and considerable psychological and financial strains on patients and their families.

These problems underscore the pressing need for resilient, automated, and clinically dependable diagnostic systems capable of facilitating early identification, precise classification, and real-time assistance for treatment planning, therefore enhancing survival rates and quality of life for patients with brain tumors.

IV. EXPECTED SOLUTION

- **Advanced Imaging and Automated Diagnosis:** Develop AI-powered MRI and CT scan analysis tools for early, accurate, and automated tumor detection and classification, reducing radiologist dependency and minimizing human errors in diagnosis.

- **Improved Tumor Segmentation Models:** Employ deep learning architectures like U-Net, DeepTumor, and hybrid CNN models for precise tumor boundary detection, aiding in surgical planning and reducing risks associated with critical brain regions.

- **Personalized Treatment Planning:** Integrate AI-based predictive analytics with patient-specific data to recommend optimal treatment strategies, including surgery, chemotherapy, and radiotherapy, improving survival rates and minimizing post-treatment complications.

- **Emerging Therapies and Targeted Approaches**: Utilize targeted therapy, immunotherapy, and tumor- treating fields alongside conventional treatments to slow tumor growth, decrease recurrence rates, and enhance quality of life for brain tumor patients.

- **Accessible and Cost-Effective Healthcare Solutions:** Develop cloud-based diagnostic platforms and low- cost AI tools for rural and under-resourced areas, ensuring early detection, timely treatment, and reducing the economic burden on patients and families.

V. CONCLUSION & FUTURE WORK

Brain tumors' complexity, variety, and influence on brain function make them one of the most difficult neurological conditions. Early identification and exact categorization remain significant problems that affect patient outcomes despite diagnostic imaging and therapy advances. Though necessary, MRI and CT scans are time- consuming and rely on professional interpretation, which might delay or misdiagnose. Recent study shows that deep learning and AI might revolutionize brain tumor detection and therapy. Up to 99% accuracy has been achieved by models including U-Net, VGG-19, DeepTumor, and Differential Deep CNN, enhancing tumor segmentation and classification for surgical and therapeutic choices. However, insufficient annotated datasets, lack of generalizability across varied populations, and "black-box" AI models remain restrict clinical application. Multimodal treatments, including surgical excision, radiation, chemotherapy, targeted therapy, immunotherapy, and tumor-treating fields, increase survival and quality of life. AI-assisted diagnosis and individualized treatment planning may reduce recurrence and improve prognosis.
Future research should build robust, interpretable, real-time automated diagnostic systems, integrate longitudinal tumor development monitoring, and provide accessible and cost-effective solutions, especially for resource-limited settings, to fill research gaps. Medical practitioners and AI researchers must collaborate to put these advances into practical practice, boosting brain tumor patients' survival and quality of life.

REFRENCE

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