A systematic Survey on Brain Tumor Detection using Deep Learning Techniques

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Abstract: **Technological advancements have significantly transformed various domains, particularly the field of healthcare. The integration of advanced computational techniques in medical applications has improved the diagnosis and treatment of critical diseases such as brain tumors. Brain tumors are among the most serious and life-threatening neurological disorders, requiring accurate and early detection for effective treatment. Automated brain tumor detection systems are designed to differentiate between normal and abnormal brain tissues using medical imaging data. In recent years, medical image processing techniques, especially those based on Magnetic Resonance Imaging (MRI), have played a vital role in automating tasks such as feature extraction, segmentation, and classification. These approaches enable faster and more reliable tumor identification. A large number of studies have explored various methods for brain tumor detection using machine learning and deep learning techniques, with a primary focus on segmentation and classification tasks. This paper aims to provide a comprehensive analysis of brain tumor detection and classification methods developed between 2019 and 2025. The study evaluates widely used approaches and examines the effectiveness of Computer-Aided Diagnosis (CAD) systems in improving diagnostic performance. To ensure a broad and unbiased review, relevant research articles were collected from multiple scientific databases, including IEEE Xplore, ScienceDirect, PubMed, Google Scholar, and ResearchGate.**

Keywords- brain tumor, Deep learning, neural network, classification, segmentation, feature extraction, dataset.

I. Introduction

The prevalence of brain tumors is a significant factor in the global mortality rate. The GLOBOCAN 2020 study indicated that there were 308,102 new brain cancer cases, with a mortality rate of 2.5% attributed to the disease [1]. Brain tumors may be classified into four primary types: gliomas, meningiomas, pituitary adenomas, and nerve sheath tumors. The World Health Organization (WHO) classifies brain tumors based on cellular origin and activity, ranging from least to most aggressive [2]. Low-grade gliomas (LGG) (grades I and II) and high-grade gliomas (HGG) (grades III and IV) represent two principal classifications of brain tumors. The HGG exhibits fast growth, with a maximum lifespan of two years. Conversely, LGG exhibits sluggish growth and may let the individual to have an extended life expectancy. Brain tumors exhibit several features, including diverse locations, forms, and sizes, as well as weak contrast, resulting in overlap with the intensity values of healthy brain tissue [3]. These traits influence the intricacy of tumor proliferation and forecast the degree of excision during surgical planning, impacting patient management [4]. Consequently, differentiating healthy tissues from tumors and achieving precise classification is a challenging endeavor. Accurate segmentation and classification of brain tumors are essential for determining tumor size, precise location, and type. Prompt identification of malignancies is crucial for the effective treatment of brain tumors. Medical imaging methods, including computed tomography (CT), biopsies, cerebral angiography, myelography, positron emission tomography (PET), and magnetic resonance imaging (MRI), play a crucial role in the diagnosis of brain tumors owing to their non-invasive characteristics [5]. MRI and CT are the two most often used modalities. MRI offers a comprehensive scan capable of readily detecting brain tumors and other infections. CAD systems significantly assist radiologists in expediting the detection of brain tumors, thereby reducing the death rate associated with brain cancer. The primary objective of the CAD is to automate the detection of brain tumor pictures with enhanced accuracy and dependability. The identification, categorization, and segmentation of brain tumors have been the subject of several publications [6]. The bulk of prior research focused on traditional and machine learning methodologies. Machine learning (ML) methodologies are particularly adept at tackling the complexities of huge data, shown by brain tumor segmentation. Nonetheless, it has been used to teach robots for picture identification, which typically requires human participation and intellect [7]. Conventional machine learning approaches use human-engineered feature extraction algorithms to distinguish tumor characteristics in imaging data [8]. Deep learning autonomously extracts significant characteristics, analyzes patterns, and classifies information via the extraction of multi-level features. Lower-level characteristics include corners, edges, and fundamental forms, while higher-level features comprise picture texture, more refined shapes, and specific image patterns [9]. Furthermore, deep learning methodologies are used to derive characteristics from supplementary data and incorporate them into the recommendation system [10]. Nevertheless, it fails to preserve spatial coherence and visual distinction of the topic. Consequently, the research paradigm for the detection, segmentation, and classification of brain tumors has transitioned towards hybrid-based methodologies. The primary contribution is to demonstrate the evolution of soft computing, namely artificial intelligence (AI), within the domain of brain tumor analysis, from both application-driven and methodological viewpoints.

II. SURVEY ON DEEP NEURAL NETWORKS FOR BRAIN TUMOR DETECTION

Several deep learning architectures have been proposed in recent years to improve the accuracy of brain tumor detection. In [11], an enhanced residual network was developed by incorporating additional layers into the backbone structure, allowing improved feature extraction. The use of the Swish activation function instead of ReLU further contributed to better feature representation and information retention.

In another study [12], well-known convolutional neural network (CNN) models such as VGG-19 and AlexNet were employed for feature extraction, and the extracted features were utilized to construct datasets for statistical evaluation. Similarly, the Siamese Convolutional Neural Network (SiCNN) introduced in [13] improved diagnostic performance by learning similarity between image pairs.

To address data privacy concerns, a federated learning-based approach was proposed, where a peer-to-peer framework enables classification of brain tumors from MRI data without sharing sensitive patient information. In [14], the ResNet50 architecture was applied using a balanced dataset consisting of MRI images from both tumor-affected and healthy individuals, demonstrating improved robustness in real-world scenarios.

Another approach [15] utilized the VGG16 model, which is known for its depth and strong performance in image classification tasks. The model effectively distinguishes between normal and abnormal brain tissues using both MRI and microscopy data. In [16], a hybrid model combining ResNet50 and EfficientNet was developed, along with data augmentation techniques to improve dataset diversity and overall performance.

Further improvements were introduced in [17], where optimized CNN and Artificial Neural Network (ANN) configurations were used along with dimensionality reduction techniques such as MPCA to enhance feature efficiency. In [18], a multi-path CNN architecture was designed to capture both local and global features, followed by a segmentation stage that utilizes skip connections for better accuracy.

A sequential CNN model was proposed in [19], incorporating convolutional, pooling, and dropout layers, followed by fully connected layers for classification. In [20], a correlation learning mechanism (CLM) was introduced to integrate CNNs with traditional deep learning structures, improving the selection of convolutional and pooling parameters.

In [21], a parallel deep CNN (PDCNN) architecture was developed to extract both global and local features simultaneously, while techniques such as batch normalization and dropout were used to reduce overfitting. Another study [22] applied CNN-based models to classify brain tumors into four categories: normal, glioma, meningioma, and pituitary tumors, addressing challenges faced in early diagnosis.

In [23], an EfficientNetv2-based model combined with Ranger optimization and extensive preprocessing techniques was proposed to improve diagnostic performance. Noise reduction using adaptive filtering [24], along with feature extraction methods such as Gray Level Co-occurrence Matrix (GLCM) and Improved K-means Clustering (IKMC), further enhanced classification accuracy.

Additionally, region-based convolutional neural networks (RCNN) and optimization techniques such as Particle Swarm Optimization (PSO) were utilized in [25] to improve segmentation and classification. Pre-trained models like Inception-V3 and AlexNet were also enhanced using transfer learning, where features from multiple models were combined to achieve better results. Finally, in [26], a neural network-based classifier was developed to predict class labels based on extracted numerical features, contributing to improved classification performance.

TABLE I. SUMMARIZATION OF VARIOUS NEURAL NETWORKS

Author/year	**Method**	**dataset**	**Results**
Khan et al., (2025)	Backbone network	BR35H binary dataset Figshare multiclass dataset	BR35H binary dataset= 99.83% Figshare multiclass dataset = 96.95%
AlShowarah et al., (2025)	CNN		accuracy= 99.1%
Onaizah et al., (2025) [13]	SiCNN	MRI images	Accuracy= 0.9711
Rath et al., (2025) [14]	ResNet50	MRI images	Accuracy= 97.35 %
Kothadiya et al., (2025) [15]	VGG19 model	MRI images	Accuracy= 98.81%
Rao et al., (2024 [16]	ResNet50 and EfficientNet	MRI images	Accuracy= 96.5%
Ye et al.,(2024) [17]	CNN+ANN	BRATS2014 and BTD20	accuracy of 98.6 % and 99.1 %,
Abd-Ellah et al., (2024) [18]	CNN	BraTS 2017	Accuracy=99%
Alshuhail et al., (2024) [19]	sequential CNN	MRI images	Accuracy =98%
Woźniak et al., (2023) [20]	CLM+CNN	CT images	Accuracy=965
Rahman et al., (2023) [21]	PDCNN	binary tumor identification dataset-I, Figshare dataset-II, and Multiclass Kaggle dataset-III	accuracy of 97.33%, 97.60%, and 98.12%
Mahjoubi et al., (2023) [22]	CNN	Kaggle dataset	95% of recall, 95.44% accuracy and 95.36% of F1-score.
Anagun et al., (2023) [23]	EfficientNetv2s	MRI dataset	Accuracy= 99.85%
Vankdothu et al., (2022) [24]	RCNN	MRI images	95.17% accuracy
Ali, et al., (2022) [25]	PSO+RCNN	BRATS-2018 and BRATS-2017	99.0% accuracy
Ahmadi et al., (2021) [26]	FWNNet	MRI images	Accuracy=87.6%

III. Survey on 3D and Volumetric Analysis

3D and volumetric analysis explores techniques for reconstructing and analyzing three-dimensional structures from medical imaging data. It focuses on methods for volume estimation, segmentation, and visualization used in diagnostics and treatment planning.

VcaNet segments 3D using Vision Transformer (ViT) and a spatial attention module (CBAM) [27]. VcaNet encoder extracts local volumetric features using 3D enhanced convolution (ENCO) module, whereas bottleneck captures global dependencies using Vision Transformer and multi-scale feature fusion module. In [28], a two-dimensional volumetric convolutional neural network was constructed. Furthermore, to forecast survival rates, radiomic characteristics from the segmented tumor locations will be used, followed by using a Deep Learning Inspired 3D replicator neural network to discern the most efficacious features. In [29] Duo-step optimised Pyramidal SegNet has been proposed in which multiscale contrast convolutional attention module improve contrast and the tumor edge has been extracted based on location and tumor extension using Duo-step darning needle optimisation that set initial contour points and pyramidal level set segmentation with ancillary Sobel edge operator extract the tumour region from all 2D MRI image slices without having overlapped tissue intensity distributions thereby effectively minimises segmentation error. Multi-modal magnetic resonance imaging is used to segment brain tumors in a hybrid advanced 3D model [30]. The model uses 3DU-Net and V-Net encoder features at every level. These features are concatenated and fused at each decoder level to build key features, followed by a 3D convolution layer and Transformers block for context. It takes a last convolutional block to segment the tumor. The SDV-TUNet encoder-decoder design included voxel, inter-layer feature, and intra-axis data [31]. The sparse dynamic (SD) encoder–decoder and multi-level edge feature fusion (MEFF) modules of a 3D network densely forecast volumetric data using extended depth modeling. An innovative 2D-3D approach was created in [32] to merge a 2D brain image with a Learnable Weighted image gradient. The proposed model seamlessly forwards the fused 3D image via a pre-trained 3D model via 2D-to-3D conversion, outperforming previous 3D baselines. The implementation employed VGG16 for feature extraction since it outperformed other 3D CNN backbones. In [33], a lightweight customized 3D UNet architecture known as Yaru3DFPN demonstrates exceptional performance. The architecture uses UNet. ResNet is upgraded with pre-activation and GroupNormalization for batch normalization. The histogram and symmetry studies in [34] automatically estimated tumor volume. Histogram distances between T1- and T1C-weighted brain MR images were used to adaptively derive skull stripping thresholds. For complete tumor identification, FLAIR pictures were used to analyze left and right brain lobe symmetry. The study [35] examined morbidity and volumetric efficacy of second-look surgery in a pediatric neuro-oncology hospital. Measurements were conducted on early postoperative magnetic resonance imaging, comparing axial diameter measurements with computer-assisted volumetric analysis. In [36], a tailored 3D U-Net model was constructed to analyze 3D volumetric images for multiclass tumor segmentation. This framework is adjusted to enhance gradient flow for achieving precise output.

IV. Survey on segmentation of Brain Tumor

The manual segmentation of tumors from MRI images is labor-intensive, subjective, and susceptible to inter-observer variability. Automated brain tumor segmentation has garnered considerable interest among the scientific community to tackle these problems. This method include the detection and definition of tumor sub-regions, including enhancing tumor, tumor core, and edema. Throughout the years, a diverse array of image processing techniques, conventional machine learning methods, and, more recently, deep learning-based approaches have been investigated.

In [37], a semisupervised cross nnU-Net using depthwise separable convolution (SSC nnSU-Net) was created for real-time segmentation of 3D iUS pictures, employing two networks with distinct initializations but a consistent network architecture. The results show that the proposed design balances computing time, GPU memory utilization, and segmentation efficiency. In [38] designed hierarchical multiscale deformable attention module (MS-DAM). MS-DAM outperformed modern multi-scale channel attention modules by 96.5%. In [39], Multiscale Attention U-Net with EfficientNetB4 encoder increase segmentation. The Multi-Scale Attention Mechanism defines tumor borders at several scales utilizing 1x1, 3x3, and 5x5 kernels, improving feature representation over CNN-based segmentation. The multitasking Wasserstein Generative Adversarial Network U-shape Network++ is presented in [40]. The Residual Attention U-shaped Network (RAUNet) model improves brain tumor segmentation accuracy by combining U-Net's feature extraction abilities with transformers' global context awareness. Diffusion Probability Model underpins BTSegDiff [41]. It created an encoder-equipped dynamic conditional guidance module. This encoder assists the DPM in creating accurate segmentation masks from multimodal MRI images. Brain pictures were automatically categorized into four categories by a deep CNN architecture and U-Net segmentation model in [42]. RMAP ResNet is recommended for the segmentation of residual and tumorous tissue [43]. Multiple effective associative receptive fields are employed by the RMAP. Locate targets that are multidimensional using these fields. They implemented a deep convolutional neural network encoder-decoder architecture [44]. We suggest semantic segmentation that is based on the EfficientNetB7 encoder and the ingenious LinkNet-34. The Enhanced Residual Network is demonstrated to be effective in the segmentation of brain tumors in [45]. ResNet may be enhanced by either retaining all connection links or enhancing projection shortcuts. Attention Res-UNet with Guided Decoder is a deep learning generator that is introduced in [46]. The learning of the decoder layer may be facilitated by the generator design that has been proposed. Learning is supervised by the loss function on each decoder layer, which improves feature maps. In [47], a 3D U-Net model was created using 3D brain imaging data. This model includes cost-effective pretrained 3D MobileNetV2 blocks and attention modules, as well as numerous skip connections. In [48], a Hybrid Attention-Based Residual Unet adaptively learned attention-aware features in local and global receptive fields using Attention and Squeeze-Excitation (SE) modules at distinct levels. In [49], AGSE-VNet, an automated brain tumor MRI data segmentation system, is introduced. In this investigation, encoders with Squeeze and Excite (SE) modules and decoders with Attention Guide Filter (AG) modules are implemented. The attention mechanism is employed in channel interactions to concentrate edge information and reduce noise, automatically enhancing essential input and attenuating irrelevant data.

V. Datasets for Brain Tumor Detection and Segmentation

Brain tumor datasets play a crucial role in the development and evaluation of machine learning (ML) and deep learning (DL) models for automated diagnosis and segmentation. These datasets enable researchers to train algorithms for accurate tumor detection, classification, and volumetric analysis. However, a detailed analysis of available datasets reveals significant variations in terms of imaging modalities, annotation quality, and clinical diversity.

Most datasets are based on imaging techniques such as Magnetic Resonance Imaging (MRI) and Computed Tomography (CT), with MRI being more commonly used due to its superior soft tissue contrast. The annotation process also differs across datasets, ranging from manual expert labeling to semi-automated approaches. Additionally, variations in tumor types, grades, and patient demographics contribute to the complexity of model development.

Several publicly available datasets, including BraTS, TCIA, REMBRANDT, and Figshare glioma datasets, are widely used as benchmarks in brain tumor research. These datasets support various tasks such as segmentation, classification, detection, and survival prediction. Despite their importance, challenges such as limited labeled data, class imbalance, and variability in expert annotations still persist. Recent research trends aim to address

TABLE II. SUMMARIZATION OF VARIOUS SEGMENTATION METHODS

Author/year	Method	Dataset	advantage	disadvantage
Li et al., (2025)	SSC nnSU-Net	hybrid dataset	Reduces computation time and GPU memory	limited generalization without diverse training samples
Zarenia et al., (2025)	MS-DAM	Kaggle dataset	High accuracy	Computationally complex; increased training time
JS et al.,(2025)	U-Net with the EfficientNetB4 encoder	Figshare brain tumor dataset	Enhanced feature extraction at multiple scales; better boundary delineation	High memory requirement due to EfficientNetB4 backbone
Lyu et al., (2025)	MWG-UNet++	Kaggle dataset	Combines strengths of GANs and U-Net++; robust global and local feature learning	GAN training instability; longer convergence time
Qin et al., (2025)	BTSegDiff	BraTs2020 and BraTS2021	Uses DPM to generate realistic segmentation masks; dynamic conditional guidance from multimodal MRI	Complexity in DPM training
Akter et al., (2024)	U-Net	six datasets	simple architecture with consistent performance	Limited capacity in complex tumor segmentation
Fan et al., (2024)	RMAP ResNet	mouse tumor	Residual attention with multi-core pooling enhances detection of tumors of different sizes	Validated only on mouse data; limited applicability to human MRI data
Sulaiman et al., (2024)	LinkNet-34+ EfficientNetB7	Kaggle dataset	Lightweight encoder-decoder structure	limited interpretability
Aggarwal et al., (2023)	ResNet	BRATS 2020 MRI	improved residual shortcut mechanisms	Performance may saturate on very deep networks
Maji et al., (2022)	ARU-GD	Github dataset	Improved performance	Decoder-layer-specific loss may increase complexity and training time
Nodirov et al.,(2022)	3D U-Net	BraTS-2020	Cost-efficient 3D segmentation with pretrained lightweight backbone	Reduced accuracy for very small tumor regions due to lightweight features
Khan et al., (2023)	HA-RUnet	BraTS-2020	Attention and SE modules improve local/global feature adaptiveness	Multiple attention modules increase model complexity
Guan et al., (2022)	AGSE-VNet	BraTS2020	Combines SE and AG modules to suppress irrelevant info and enhance edge accuracy	increased resource requirements during inference

these issues through techniques like multimodal data fusion, synthetic data generation, and federated learning to ensure privacy-preserving data sharing.

The Brain Tumor Segmentation (BraTS) dataset [50] is one of the most widely used benchmarks for evaluating tumor segmentation models. It consists of multi-contrast MRI scans of glioma patients, including both low-grade and high-grade tumors. The dataset was collected from multiple medical institutions over several years, ensuring diversity in imaging conditions and patient profiles. It includes various MRI sequences such as T1-weighted, contrast-enhanced T1 (T1c), T2-weighted, and FLAIR images, which provide complementary information for accurate tumor analysis.

Another important dataset is the Figshare Brain MRI dataset [51], which contains a large number of MRI slices collected from multiple hospitals. It includes images of different tumor types such as meningioma, glioma, and pituitary tumors. The dataset provides high-resolution images and is commonly used for classification and detection tasks in deep learning applications.

Additionally, datasets available on platforms like Kaggle [52] offer labeled MRI images for binary classification tasks, distinguishing between tumor and non-tumor cases. These datasets are generally preprocessed, including skull stripping and normalization, making them suitable for initial model development and experimentation.

Overall, the availability of diverse datasets has significantly contributed to advancements in brain tumor detection. However, improving data quality, increasing dataset size, and ensuring standardized annotations remain key areas for future research.

Several public datasets were used to test the approaches. This section covers various important and complex datasets. The hardest MRI datasets are BRATS. Table 3 summarizes dataset names.

TABLE III. SUMMARY ON DATASETS

Dataset	MRI sequence	Reference
BRATS	T1, T2, FLAIR	[53]
RIDER	T1, T2, FLAIR	[54]
Harvard	T2	[55]
TCGA	T1, T2, FLAIR	[56]
Figshare	T1	[57]
IXI	T1 ,T2	[58]

TCGA-GBM dataset [56] - TCGA-GBM contains molecular and clinical data on the most common and lethal primary brain tumor, glioblastoma multiform. National Cancer Institute gathered approximately 500 GBM patients' medical data. The dataset contains imaging, genomic, and clinical data. Pre- and post-surgery T1- and T2-weighted MRI images are included. Clinical information includes patient, tumor, and therapeutic facts. Research on brain tumor diagnosis, therapy, and prognosis and machine learning algorithm segmentation and classification have significantly exploited the TCGA-GBM dataset. The enormous and diverse dataset available to create and test new ideas and algorithms has greatly assisted research in this field. The dataset is provided in DICOM, NIFTI, and CSV formats and contains metadata and instructions for data analysis.

BraTS 2018 and 2019 dataset - The BraTS 2018 dataset includes 285 HGG and 66 LGG instances [59]. BRATS 2019 has 460 instances, 335 of which are HGG and 125 LGG. These examples were acquired using the same MRI sequences as last year. MRI sequences included T1-weighted, T1-weighted with gadolinium contrast enhancement, T2-weighted, and FLAIR. Images were normalized to 1 mm3 isotropic voxels (240 × 240 × 155). Enhanced, non-enhancing, and edema segmentation masks and a whole tumor area are included in the dataset which is available in NIfTI.

IXI dataset [58] - Datasets may increase research accuracy. This BRAINIX dataset is confined to certain individuals. The DICOM library set handles this dataset privately. Only special clearance holders may see this dataset.

VI. EVALUATION METRICS

- Dice score- Often, the Dice coefficient is used to compare expected and actual segmentations. It is described below [60]:

$$dice(X,Y) = \frac{2|X \cap Y|}{|X| + |Y|}$$

The predicted and ground truth segmented voxels are x and y. X∩Y is the intersection of x and y. If dice coefficient is 1, expected and ground truth segmentations match entirely.

- Hausdorff distance- Most significant difference between anticipated and ground truth segmentations indicates segmentation accuracy as [61]:

$$dh(X,Y) = max\left\{\min_{x \in X} d(X,Y) \min_{y \in Y} \mathrm{d(X,Y)}\right.$$

where the predicted and ground truth segmentation voxels are x and y. The Function $d(x,y)$ represents segmentation points x and y.

- Sensitivity: It quantifies the ratio of accurately detected true positives, as defined by [62]:

$$sensitivity = \frac{tp}{tp + fn}$$

True positives are tumor voxels correctly identified, whereas false negatives are tumor voxels misclassified as non-tumor. Sensitivity is indicative of a greater capacity to identify tumor voxels.

- Specificity: Specificity quantifies the ratio of accurately detected true negatives, as defined by [62]:

$$specificity = \frac{TN}{TN + FP}$$

True negatives refer to the quantity of non-neoplastic voxels accurately recognized as such, whereas false positives denote the amount of non-tumor voxels erroneously categorized as tumor voxels. The capacity to differentiate between tumor and nontumor voxels is stronger when the specificity is higher.

VII. Challenges in Deep Learning-Based Tumor Detection

Deep learning for brain tumor detection using MRI images is impeded by several challenges that impact its precision, reliability, and practical use. The problems arise from the data, used model, domain, computational processes, discrepancies in assessment standards, and clinical issues.

- The lack of large, excellent, well labeled brain tumor datasets is a significant issue. This arises from the rarity of certain tumor forms, patient confidentiality issues, and the cost associated with expert radiologist annotation [63]. The model may also be affected by class imbalance (biased tumor types), data heterogeneity (MRI scanners, protocols, resolutions, and imaging modalities including T1, T2, FLAIR, and DWI), and scan noise and artifacts.
- DL might be challenging for diagnosing brain tumors due to model issues. The form, size, location, and texture of tumors make tumor detection model training problematic. Complex processing is needed for 3D volumes with several modalities in MRI data. Training data shortages cause overfitting and impede data generalization. Combining T1, T2, and FLAIR data to enhance efficacy introduces an additional layer of complexity. The "black box" models limit clinician confidence and interpretability. Ultimately, attaining effective generalization across varied datasets, imaging devices, and patient demographics continues to be a significant challenge [64].
- Segmentation and categorization of brain tumors are difficult due to their different histological characteristics, such as necrosis, edema, and enhancing/non-enhancing zone. Moreover, precisely delineating tumor margins, especially for infiltrative gliomas, poses significant challenges and may be subjective, even for seasoned radiologists.
- MRI data needs rigorous preprocessing processes (e.g., skull stripping, normalization, registration) for consistency, yet these methods are error-prone. Deep learning on 3D MRI data requires high-memory GPUs. It is challenging to integrate T1, T2, FLAIR, and DWI MRI data to improve diagnostic precision. Researchers are using hardware accelerators like FPGAs to reduce inference times to incorporate deep learning models into healthcare workflows for faster diagnosis.

VIII. Future Scope

- Deep learning is a common approach for MRI data brain cancer detection and segmentation. DeepMedic, V-Net, and U-Net can segment brain tumors in 3D [65]. Modifying CT and MRI models and merging data from many imaging sources has increased their use. AI models using imaging (MRI, CT), genomic (DNA/RNA sequencing), and clinical (patient history, treatment responses) data understand cancers. This multimodal method enhances tumor categorization and personalized treatment [107]. Recent research reveal that enhanced deep learning architectures that integrate structural MRI sequences (T1, T2, and FLAIR) with functional imaging and genetic biomarkers improve diagnostic performance.
- Lightweight deep learning models effectively detect brain cancers on limited resources. These approaches provide quick treatment with real-time diagnosis and monitoring on edge devices. Malignant tissue is being identified during brain tumor surgery using intraoperative AI-assisted methods to enhance results. FastGlioma leverages artificial intelligence and stimulated Raman histology (SRH) to diagnose tissue samples in seconds with high accuracy [66].
- AI models are increasingly emphasized for explainability and transparency, boosting physician trust in addition to efficiency. In addition to efficiency improvements, AI models are becoming more explainable and open to boost clinician trust. Explainable AI (XAI) mitigates the medical AI "black box" issue by making deep learning models for brain tumor detection more interpretable. Grad-CAM and attention methods showcase the model's most important picture areas, boosting transparency and prediction accuracy [67].
- The regulatory environment for AI in healthcare is becoming standardizing. Structured challenges and public datasets like BraTS have spurred research and defined criteria for assessing deep learning methods. The standardization of imaging methods and annotation rules enhances the consistency and dependability of these models.

IX. Conclusion

This paper presented a comprehensive survey of recent advancements in brain tumor detection, segmentation, and classification using deep learning techniques. Various approaches based on convolutional neural networks, hybrid models, and transformer-based architectures were analyzed to understand their effectiveness in medical image processing. The study highlights how deep learning methods have significantly improved the accuracy and automation of tumor analysis compared to traditional techniques. Despite these advancements, several challenges still remain, including difficulty in accurately identifying tumor sub-regions, handling class imbalance, and ensuring robustness across diverse datasets. Variations in imaging conditions and limited availability of high-quality annotated data further impact model performance. This survey also emphasizes the importance of integrating advanced techniques such as multimodal learning, 3D volumetric analysis, and attention-based models to enhance diagnostic accuracy. Future research can focus on developing more generalized and interpretable models, as well as incorporating privacy-preserving frameworks such as federated learning. Overall, this work provides a structured understanding of existing methodologies, their limitations, and potential research directions, which can assist researchers in designing more efficient and reliable brain tumor detection systems.

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