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Attention-based deep learning approaches in brain tumor image analysis: A mini review

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ABSTRACT

Introduction: Accurate diagnosis is crucial for brain tumors, given their low survival rates and high treatment costs. However, traditional methods relying on manual interpretation of medical images are time-consuming and prone to errors. Attention-based deep learning, utilizing deep neural networks to selectively focus on relevant features, offers a promising solution.

Material and Methods: This paper presents an overview of recent advancements in attention-based deep learning for brain tumor image analysis. While the reviewed models have demonstrated respectable performance across different datasets, they have yet to achieve state-of-the-art results.

Results: Advanced techniques, including super-resolution image reconstruction, multi-swin-transformer blocks, and spatial group-wise enhanced attention blocks, have shown improved segmentation network performance. Integration of graph attention, swin-transformer, and gradient awareness minimization with positional attention convolution blocks, self-attention blocks, and intermittent fully connected layers has considerably enhanced the efficiency of classification networks.

Conclusion: While attention-based deep learning has shown improvements in performance, challenges persist. These challenges include the requirement for large datasets, resource limitations, accurate segmentation of irregularly shaped tumors, and high computational demands. Future studies should address these challenges to further enhance the efficiency of brain tumor diagnoses in real-world settings.

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INTRODUCTION

Brain tumors (BTs), particularly glioblastoma, present a substantial health challenge, characterized by a 5-year survival rate of less than 10% and average treatment costs amounting to US $62,606 [1]. BTs encompass cancerous lesions that can originate from various cells within the brain or surrounding tissues, including the meninges, pituitary gland, and pineal gland. The diagnosis of BTs poses challenges due to their considerable histological and genetic heterogeneity, as well as the potential for both benign and malignant variants [2].

BTs span a spectrum ranging from slow-growing tumors with a favorable prognosis (low grade) to the most aggressive and life-threatening forms (high grade). Accurate assessment of the characteristics associated with each grade is crucial for determining appropriate treatment strategies and predicting patients' prognosis [3]. These tumors are associated with a diverse range of neurological and cognitive symptoms, significantly impacting overall health and quality-adjusted life years, particularly among younger individuals [4].

Medical imaging modalities, including computed tomography (CT), magnetic resonance imaging (MRI), and positron emission tomography (PET), have emerged as powerful tools for assisting in the diagnosis of BTs [5]. The application of machine learning (ML) and deep learning (DL) techniques has had a significant impact on the field of medical image computing, enhancing the accuracy and efficiency of disease diagnosis and treatment [6-9]. For example, DL models such as AlexNet [10], VGGNet [11], ResNet [12], and DenseNet [13] have demonstrated promising results in the analysis of BT images [14]. Moreover, attention-based deep learning (ADL) has been recently introduced to augment medical image classification and segmentation. By selectively focusing on relevant information and disregarding irrelevant information, ADL models applied to BTs improve tumor detection accuracy and reliability compared to non-ADL methods [15, 16].

MATERIAL AND METHODS

Medical imaging techniques for brain tumors diagnosis

Identification of BTs is crucial for providing optimal treatment and improving patient outcomes. A deeper understanding of the underlying mechanisms of BTs and advancements in medical diagnostic tools have contributed to more effective prognoses.

Table 1 summarizes various medical imaging modalities used for BT detection, including histopathological imaging (HI), CT, PET, and MRI [17]. These modalities are commonly employed, but except for MRI, they may not provide a comprehensive view of all aspects and areas of BTs [18].

MRI is a commonly used medical imaging modality in clinical practice due to its high resolution, effectiveness in detecting BTs, non-invasive nature, and lack of harmful radiation. MRI is also capable of detecting a variety of nervous system diseases. While there may be potential challenges such as patient discomfort during scans, MRI remains an affordable and suitable imaging modality [18]. This is due in part to the availability of large-scale public datasets (e.g., BraTS, Figshare, TCIA, IBSR, NBIA, FeTS, etc.), which provide researchers with a wealth of information to improve the accuracy of MRI [19]. MRI offers important clinical value for the diagnosis and monitoring of BTs, thanks to its high resolution, multi-planar imaging, contrast-enhanced imaging, and non-invasive nature.

Fig 1 shows the most commonly used MRI sequences in BT diagnosis: Fluid Attenuated Inversion Recovery (FLAIR), T1-weighted (T1-w), T2-weighted (T2-w), and Contrast-enhanced T1-weighted (CeT1-w). Gadolinium-enhanced MRI is also typically used in BT diagnosis to assist with assessment of tumor extent, identification of tumor recurrence, and monitoring treatment responses [20]. High-resolution, 3-dimensional imaging is now becoming standard.

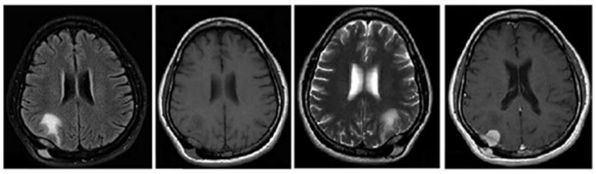

Fig 1: Schematic of the FLAIR, T1-w, T2-w, and CeT1-w in brain tumors detection

Recent developments in MRI offer new opportunities for providing microstructural, hemodynamic, and metabolic information and assessing tumor vascularity and hemodynamics in the context of BT studies. Diffusion-weighted imaging and susceptibility-weighted imaging are valuable tools for the differential diagnosis of leptomeningeal metastasis and areas of hemorrhage or calcifications [21]. Techniques such as diffusion tensor imaging and tractography are useful in determining the relationship of the tumor to major white matter tracts and can help guide the surgical approach. Magnetic resonance spectroscopy aids in the differential diagnosis and grading of BTs, while functional MRI can non-invasively map eloquent areas during tasks, assisting in planning the extent of tumor resection [22].

Attention-based deep learning for brain tumors diagnosis

ADL harnesses the power of deep neural networks to automatically learn complex spatial and contextual relationships from medical pixel data, enabling more accurate and efficient tumor delineation for various tasks such as segmentation, classification, and detection [23]. Attention mechanisms in DL models allow for selective focus on relevant image regions while suppressing irrelevant or noisy areas [24]. By dynamically allocating computational resources to regions of interest, attention-based models demonstrate superior performance for BT image analysis. ADL models excel at capturing long-range dependencies and contextual information, facilitating an understanding of the tumor environment and aiding in precise tumor boundary delineation.

Attention mechanisms in DL involve mathematical and statistics operations, such as matrix multiplication, dot product, Softmax function, and scaling factor, to selectively focus on relevant parts of input data. The formula for attention mechanisms is represented as

$$Attention\ (Q * K * V) = Softmax\left(\frac{QK^T}{\sqrt{dk}}\right) \times V \qquad (1)$$

where Q, K, and V are the query, key, and value matrices, respectively. The dot product of the query and key matrices is divided by the square root of the dimension of the key matrix (dk) to scale the attention weights. The resulting attention weights are then normalized using the Softmax function to obtain a set of weights that sum to one. Finally, the attention weights are multiplied by the value matrix to obtain the final output. The scaling factor is an essential component of the attention mechanism, as it ensures that the attention weights are appropriately scaled.

The channel attention mechanism is commonly used for both BT classification [25] and segmentation [26]. It adjusts the weight of individual input channels based on the assumption that different channels often represent separate objects in an image [27]. Recent studies have shown that channel attention can be further improved by fusing it with attention augmentation mechanisms that use both convolutions and self-attention. This is achieved by concatenating convolutional feature maps with a set of feature maps generated by self-attention [28], resulting in even better performance of the model in BT image analysis [29]. Spatial attention is another attention mechanism commonly used in BT segmentation [30]. It selectively assigns weights to different regions of the input image based on their relevance to the task at hand [31].

Global attention [32], primarily used for classification tasks, considers the entire image for feature extraction. Branch attention [33] formulates an attention mask across different branches, which can then be used to identify the salient branches [15]. Temporal attention [34] adjusts an attention mask over the temporal dimension, which can then be harnessed to distinguish vital frames of the input data. By employing this attention mechanism, the model is enabled to concentrate on the most salient temporal segments while disregarding irrelevant ones. Cross-attention [35] allows one set of features to selectively attend to another set of features, enabling the model to focus on the most relevant information from the second set of features while processing the first set. Local attention [35], used for segmentation tasks, enhances efficiency and reduces the computational burden of processing voluminous medical images, which may consist of numerous pixels/voxels, by selectively focusing on a compact, predetermined region of the image in proximity to the current location of the attention mechanism. Additionally, hybrid attention [36], such as multimodal attention mechanism, can combine a variety of attention forms for better performance and interpretability in both segmentation and classification tasks. Channel attention, hybrid attention, and self-attention are the most commonly used attention mechanisms in recent studies [23].

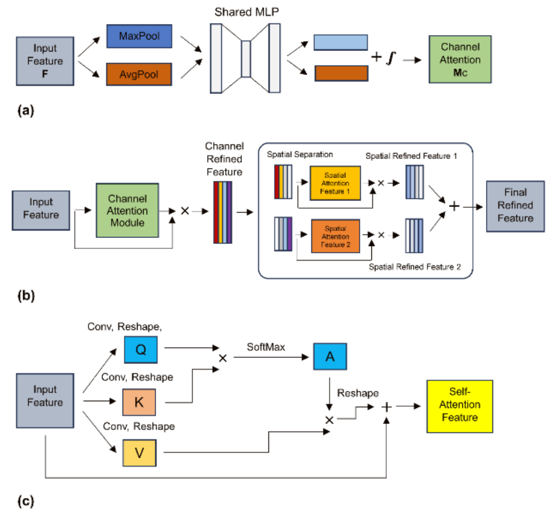

Fig 2: The architecture of (a) Channel attention, (b) Hybrid attention, (c) Self-attention

Table 1: Summary of various medical imaging modalities for brain tumors diagnosis

Modality	Mechanism	Advantage	Disadvantage	Ref
HI	Biopsy or surgical resection tissue samples are examined under a microscope using staining techniques such as hematoxylin and eosin staining, immunohistochemistry, and in situ hybridization.	The clinical gold standard Improving efficiency in the brain tumors diagnosis by emerging digitization Detecting specific molecular markers and genetic mutations through molecular imaging Guiding personalized treatment	Invasive method Requiring tissue samples Time-consuming	[37]
PET	Uses a radiotracer (e.g., 18F-2-fluoro-2-deoxy-D-glucose) to identify different types of tumors, evaluate severity, identify the extent of involvement, and monitor recovery progress.	Non-invasive method Detecting nervous system diseases	More expensive than MRI Less available than MRI Needing a radioactive tracer More radiation exposure	[38]
CT	Uses X-rays to produce cross-sectional images of brain and other tissues.	Providing information about the size and location of brain tumors, also the presence of calcifications or hemorrhages.	Using ionizing radiation Les resolution than MRI	[39]
MRI	Uses magnetization and microwave pulses to visualize internal body structures. Scans are performed on a 1.5 or 3 Tesla scanner and include various sequences and procedures.	Non-invasive method High-resolution capability No harmful radiation Large-scale public datasets Affordability and suitability	Patients undergoing MRI scans may be experiencing pain and/or other symptoms.	[19, 40]

Table 2: Summary of various studies on attention-based deep learning for brain tumors segmentation

Study	Mechanism	Method	Data	Modality	DSC		
					WT	TC	ET
[15]	3D CNN with Shuffle Attention and Multi-Branch Attention	3D MBANet	BraTS 2018	MRI	89.8%	85.47%	80.18%
		3D MBANet	BraTS 2019	MRI	89.79%	83.04%	78.21%
[41]	3D Model with Multi-Scale Attention Fusion and Dual Path Convolution	3D DPAFNet	BraTS 2018	MRI	90.0%	83.9%	79.5%
		3D DPAFNet	BraTS 2019	MRI	89.0%	81.2%	78.2%
[42]	Multiscale Lightweight 3D U-Net with Dilated Hierarchical Decoupled Convolution	3D ADHDC-Net	BraTS 2019	MRI	89.94%	83.89%	77.91%
[43]	Focal transformer with Fine-Grained Local Self-Attention and Coarse-Grained Global Self-Attention	FC-Transformer	BraTS 2021	MRI	93.28%	87.35%	87.28%
[44]	3D Transformer with Fusion-Head Self-Attention mechanism and Infinite Deformable Fusion Transformer Module	3D Brainformer	BraTS 2017	MRI	89.4%	80.3%	74.2%
		3D Brainformer	BraTS 2018	MRI	89.7%	82.3%	77.8%
[45]	3D U-Net with Efficient R-Transformer Network and Dual Encoders	3D Efficient R-Transformer	BraTS 2017	MRI	83.20%	77.93%	72.59%
[33]	3D U-Net with Attention and Super-Resolution Reconstruction	3D SRRAttU-Net	BraTS 2021	MRI	91.05%	88.30%	89.61%
[46]	U-Net++ with Swin Transformer for both Local and Global Features	3D DenseTrans	BraTS 2021	MRI	93.2%	86.2%	88.3%
[47]	Swin Transformer with a Modified CNN-Encoder with Residual Blocks and a Channel Attention Module	3D CATBraTS	BraTS 2021	MRI	87.6%	79.9%	82.6%
[48]	Attention-based CNN with Pre-trained VGG16 and Attention Gate	Efficient U-Net	BraTS 2020	MRI	86.0%	90.0%	83.0%
[49]	Supervised Attention Module based on the Attention Mechanism	3D CGA U-Net	BraTS 2019	MRI	89.29%	82.32%	78.83%
[50]	U-Net with Multipath Residual Attention Block	3D Single-Level U-Net	BraTS 2018	MRI	89.59%	79.77%	77.71%
		3D Single-Level U-Net	BraTS 2019	MRI	88.48%	80.98%	74.91%
		3D Single-Level U-Net	BraTS 2020	MRI	88.57%	80.19%	72.91%
		3D Single-Level U-Net	BraTS 2021	MRI	89.33%	82.19%	77.73%
[51]	3D Swin Transformer with CNN and Encoder-Decoder	3D SwinBTS	BraTS 2019	MRI	89.75%	79.28%	74.43%
		3D SwinBTS	BraTS 2020	MRI	89.06%	80.3%	77.36%
[52]	Multiscale Contextual Attention Module combined with a Deep Residual U-Net	3D MCA ResU-Net	BraTS 2017	MRI	84.4%	85.9%	78.9%
		3D MCA ResU-Net	BraTS 2019	MRI	84.9%	86.5%	78.4%
[53]	3D U-Net with Residual Blocks and Spatial Group-Wise Enhance Attention Blocks	3D SGE ResU-Net	BraTS 2020	MRI	90.48%	85.22%	79.4%
		3D SGE ResU-Net	BraTS 2021	MRI	91.64%	86.85%	83.31%
[54]	Multimodal Attention-Gated Cascaded U-Net	3D MAC U-Net	BraTS 2018	MRI	94.47%	84.12%	82.72%
[55]	3D U-Net with Transformer-Convolution Inception, Cross-Attention Fusion with Global and Local Feature, and Skip Connection with Cross-Attention Fusion	3D TransConver	BraTS 2018	MRI	91.57%	85.68%	81.73%
		3D TransConver	BraTS 2019	MRI	90.19%	82.57%	78.40%
[56]	3D Encoder-Decoder with CNN and Dual Swin Transformer Block	3D CSU-Net	BraTS 2020	MRI	89.27%	88.57%	81.8%

DSC: Dice Similarity Coefficient, WT: Whole-Tumor, ET: Enhanced-Tumor, TC: Tumor-Core

Fig 2 demonstrates the architectures of channel attention, hybrid attention, and self-attention. Self-attention is a component of transformers that has been applied to medical vision tasks using the vision transformer architecture [57].

RESULTS

Multi-head attention and scaled dot-product modules are the core components of vision transformers [58]. Vision transformers [57] compute the correlation between image features and all pixels in an image by tokenizing the image, allowing for the weighting of different spatial locations in the image. Although vision transformers have demonstrated the superiority of pure attention-based networks over convolutional neural networks (CNN), it is important to note that vision transformers typically require a large number of parameters and significantly more computational resources than CNN-based models [59]. To address these limitations, recent studies have proposed lightweight attention modules by optimizing existing attention architectures [58]. These modules can effectively reduce computational costs and model parameters while maintaining high accuracy.

Table 2 summarizes the latest studies that have applied ADL techniques to BT segmentation. Among these studies, 27.27% were trained and evaluated on BraTS 2019, 24.24% on BraTS 2020, 18.18% on both BraTS 2018 and BraTS 2021, 9.09% on BraTS 2017, and 3.03% on FeTS 2022.

Table 3: Summary of various studies on attention-based deep learning for brain tumors classification

Study	Mechanism	Method	Data	Modality	Accuracy
[60]	Linear-Complexity Data-Efficient Image Transformer with External Attention Mechanism and Gated-Pooled Convolutional Neural Network	LCDEiT	BraTS 2021	MRI	98.11%
		LCDEiT	Figshare	MRI	93.69%
[61]	Pre-trained Vision Transformer with Residual in Multi-Head Attention Block	Novel ViT	Custom Data	MRI	96.15%
[62]	Hybrid Transformer-Enhanced Convolutional Neural Network for Local and Global Features	TE CNN	BraTS 2020	MRI	96.75%
		TE CNN	Figshare	MRI	99.10%
[63]	3D Swin Transformer	Swin Transformer	Custom Data	MRI	99.51%
[64]	Gradient Awareness Minimization with Positional Attention Convolution Block, Relative Self-Attention Transformer Block, and Intermittent Fully Connected Layer	GAM-SpCaNet	BraTS 2019	MRI	99.28%
[65]	Pre-Trained EfficientNet with Multi-Path Convolution and Multi-Head Attention Block	EfficientNetB4	TCIA	MRI	98.35%
[66]	Baseline VGG19 with Feature Fusion Modification and Attention Module	AFF-VGG19	Custom Dataset	MRI	95.53%
[25]	DenseNet-201 with Channel Attention Mechanism SENet and Deep Convolution Generative Adversarial Networks	SE-DenseNet-201	Custom Dataset	MRI	93.05%
[67]	Pre-trained and Fine-tuned Vision Transformer	ViT	Figshare	MRI	98.7%
[68]	Attentive Deep Learning with Multimodal Feature Aggregation, Attention Mechanism, and Separable Embedding, and Modal-Wise Shortcuts	AMM CNN	RSNA-MICCAI	MRI	63.71%
[69]	Multi-Level Attention with Spatial and Cross Channel and Xception Backbone	MANet	BraTS 2018	MRI	94.91%
		MANet	Figshare	MRI	96.51%
[70]	Graph Attention Auto-encoder Inspired CNN	GATE CNN	Custom Datasets	MRI	98.27%
		GATE CNN	Custom Datasets	MRI	99.83%
		GATE CNN	Custom Datasets	MRI	98.78%

The 3D SRRAttU-Net model with an average Dice similarity coefficient (DSC) of 89.65% has outperformed other models on BraTS 2021. The 3D MAC U-Net model with an average DSC of 87.10% has outperformed other models on BraTS 2018. The 3D CSU-Net model with an average DSC of 86.5% has performed best on BraTS 2020, while the 3D CGA U-Net model with an average DSC of 83.48% has performed best on BraTS 2019. Finally, the 3D MCA ResU-Net model with an average DSC of 83.07% has outperformed other models on BraTS 2017.

Table 3 summarizes recent studies that have proposed and applied ADL techniques to the task of classifying BT. The table reveals that among these studies, 23.53% conducted their training and evaluation on BraTS datasets from 2019 to 2021, 41.18% on Figshare, 23.53% on custom datasets, and 5.88% on both RSNA-MICCAI and TCIA datasets.

The GATE-CNN, Swin Transformer, and GAM-SpCaNet models achieved accuracies of 99.83%, 99.51%, and 99.21%, respectively, on the aforementioned datasets, outperforming other models.

DISCUSSION

ADL methods have revolutionized the field of BT detection in medical imaging. These methods use deep neural networks to automatically learn complex spatial and contextual relationships from medical images, while attention mechanisms selectively focus on relevant image regions. This improves the efficiency of segmentation and classification tasks. ADL models have demonstrated high potential for streamlining the standard process of automatic image analysis, improving diagnosis accuracy, and saving time and labor for medical professionals. Automated BT segmentation could also reduce inter-observer variability and enable large-scale studies. The recent ADL models reviewed here have shown good performance in BT segmentation and classification across various datasets, but they are not yet state-of-the-art. These models utilize advanced techniques such as: super-resolution image reconstruction, coordinate attention modules, group normalization with attention gates and skip-layer connections, multi-scale attention fusion, residual blocks, spatial group-wise enhanced attention blocks, and multi-swin transformer blocks. These techniques significantly enhance the performance of segmentation networks. Additionally, the following techniques have been shown to improve the efficiency of classification networks: graph attention, swin transformer, gradient awareness minimization with positional attention convolution block, self-attention block, and intermittent fully connected layer.

Notably, the vision transformer model has shown exceptional performance, achieving comparable results to CNNs in image classification tasks [71]. However, to achieve the desired level of precision, these models require a large training dataset of more than 100 million images.

Despite recent advances in ADL methods for medical image computing, accurately segmenting small and irregularly shaped BTs remains a significant challenge. Additionally, the lack of diversity in the datasets used for evaluation limits the generalizability of proposed architectures to different populations and imaging modalities.

To address these limitations, future research can focus on developing models capable of handling diverse datasets and different types of BTs while using more diverse evaluation datasets. Furthermore, developing lightweight and efficient models that can be deployed in resource-limited settings can increase the practicality of these models.

Future research can also address existing limitations by exploring the potential of combining ADL techniques with other imaging modalities to enhance the accuracy of BT classification and segmentation tasks, incorporating explainable artificial intelligence techniques to improve the interpretability of the network and provide insights into the underlying mechanisms of BT diagnosis, and integrating these techniques with other clinical data, such as genomics, to aid in personalized medicine and improve patient outcomes.

CONCLUSION

ADL methods have shown great potential in improving the efficiency of BT classification and segmentation tasks, which can aid in treatment planning and reduce inter-observer variability. Despite these benefits, accurately segmenting small and irregularly shaped tumors remains a significant challenge, and the lack of diversity in evaluation datasets limits the generalizability of proposed models. To address these limitations, future research can focus on: developing models that can handle diverse datasets and different types of BTs, creating lightweight and efficient models that can be used in resource-limited settings, integrating ADL techniques with other imaging modalities and clinical data, and using explainable artificial intelligence techniques to improve the interpretability of the network and provide insights into the mechanisms of BT classification and segmentation. Ongoing research and development in this area have the potential to advance the diagnosis and treatment of BTs, leading to better patient outcomes.

AUTHOR'S CONTRIBUTION

All authors contributed to the study's conception, roadmap, and design. The first draft of the manuscript was written by MS and all authors commented on previous versions of the manuscript. The final editing was accomplished by SL. All authors read and approved the final manuscript.

CONFLICTS OF INTEREST

The authors declare no conflicts of interest regarding the publication of this study.

FINANCIAL DISCLOSURE

No financial interests related to the material of this manuscript have been declared.

ETHICS APPROVAL

Not applicable.

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