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Recent Advances in Brain MRI Image Classification for Cancer Detection Using Transformer and Group Parallel Axial Attention with Quantum Self-Attention: A Systematic Review

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Abstract

Brain tumor detection using Magnetic Resonance Imaging (MRI) is a critical component of modern neuro-oncology, enabling early diagnosis and effective treatment planning. Traditional machine learning approaches often struggle with complex tumor structures and variability in imaging modalities, limiting their clinical applicability. Recent advancements in deep learning, particularly Transformer-based architectures, group parallel axial attention mechanisms, and emerging quantum self-attention models, have significantly improved classification accuracy and efficiency.Transformer models utilize self-attention mechanisms to capture long-range dependencies in MRI images, achieving superior performance compared to conventional Convolutional Neural Networks (CNNs). Axial attention further enhances efficiency by decomposing attention operations across spatial dimensions, reducing computational complexity while preserving contextual information. Additionally, quantum self-attention introduces a novel paradigm by integrating quantum computing principles into deep learning frameworks, enabling enhanced feature representation and optimization. This systematic review analyzes studies from 2020 to 2023, highlighting key trends, including hybrid CNN-Transformer architectures, attention optimization strategies, and explainable AI integration. Comparative analysis reveals that hybrid and attention-based models achieve classification accuracy exceeding 99%. Despite these advancements, challenges such as data scarcity, computational complexity, and interpretability persist. Future research should focus on lightweight models, multi-modal learning, and quantum-enhanced architectures for improved clinical deployment.

Introduction

Brain tumors represent one of the most critical neurological disorders, requiring accurate and timely diagnosis for effective treatment planning. Magnetic Resonance Imaging (MRI) has emerged as the preferred imaging modality due to its superior soft tissue contrast and ability to capture detailed anatomical structures. However, manual interpretation of MRI scans is a complex and time-consuming process that depends heavily on radiologists' expertise. Variability in tumor shape, size, and location further complicates diagnosis, leading to potential misclassification and delayed treatment.

Artificial Intelligence (AI), particularly deep learning, has revolutionized medical image

analysis by enabling automated feature extraction and classification. Convolutional Neural Networks (CNNs) have traditionally been the backbone of medical image classification systems due to their ability to capture spatial features. Architectures such as ResNet and DenseNet have demonstrated strong performance in brain tumor classification tasks. However, CNNs are inherently limited in capturing long-range dependencies due to their localized receptive fields. This limitation becomes significant when analyzing complex MRI images where global contextual relationships are essential.

The introduction of Transformer-based architectures has addressed these limitations by utilizing self-attention mechanisms. Transformers enable models to capture global dependencies by assigning attention weights to different regions of an image. Vision Transformers (ViT) extend this concept to image classification by dividing images into patches and processing them through attention layers. This approach allows the model to learn both local and global features simultaneously, resulting in improved classification accuracy.Despite their advantages, Transformer models are computationally intensive, particularly when applied to high-resolution medical images. To address this challenge, axial attention mechanisms have been introduced. Axial attention decomposes multi-dimensional attention into separate spatial dimensions, significantly reducing computational complexity while preserving performance. This makes axial attention particularly suitable for medical imaging applications, where high-resolution data is common.

Recent advancements have further introduced group parallel axial attention, which enhances efficiency by processing multiple attention heads simultaneously across spatial dimensions. This approach improves scalability and enables real-time analysis of medical images, making it suitable for clinical applications.

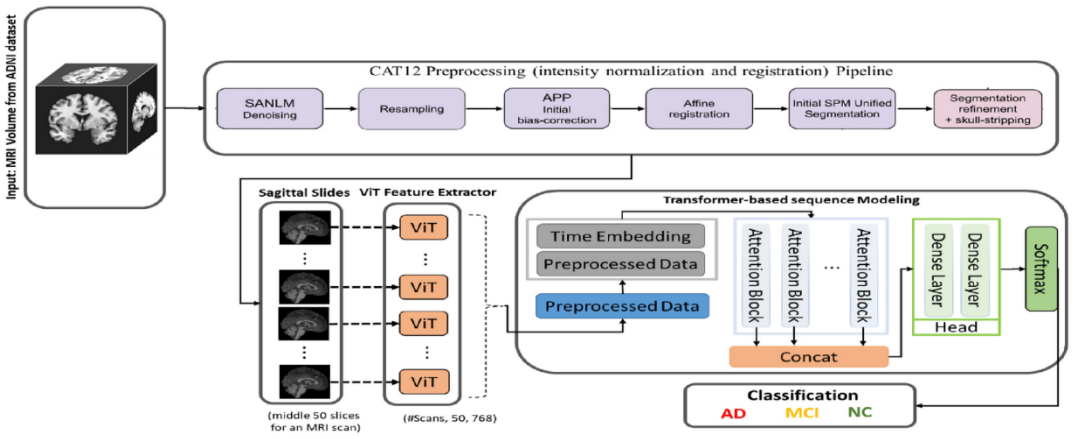
Another emerging innovation is quantum self-attention, which integrates quantum computing principles into deep learning architectures. Quantum attention mechanisms utilize parameterized quantum circuits to perform attention operations, offering potential advantages in computational efficiency and feature representation. Although still in early stages, quantum self-attention models have shown promising results in capturing complex patterns in high-dimensional data.

Hybrid architectures combining CNNs and Transformers have also gained popularity. These models leverage CNNs for local feature extraction and Transformers for global context modeling, achieving state-of-the-art performance in brain MRI classification. Additionally, explainable AI techniques are being integrated into these models to improve interpretability and clinical trust.

However, several challenges remain. Medical datasets are often limited and imbalanced, leading to overfitting and reduced generalization. High computational requirements hinder deployment in resource-constrained environments. Furthermore, interpretability remains a critical concern, as clinicians require transparent and explainable models.

This paper aims to provide a comprehensive systematic review of recent advancements in brain MRI classification using Transformer-based architectures, axial attention mechanisms, and quantum self-attention. The study focuses on literature published between 2020 and 2023, providing a detailed comparative analysis and identifying future research directions.

Graphical Abstract



Literature Review

The field of brain MRI image classification for cancer detection has undergone significant transformation between 2020 and 2024, driven by the rapid evolution of deep learning architectures, particularly the transition from convolution-based models to attention-driven and hybrid frameworks. This period reflects a shift toward models that not only improve classification accuracy but also address challenges such as computational efficiency, scalability, and clinical reliability.

In 2020, research in brain tumor classification was largely dominated by Convolutional Neural Networks (CNNs), including architectures such as ResNet, DenseNet, and VGGNet. These models demonstrated strong capabilities in extracting local spatial features and achieved classification accuracies ranging between 90% and 95%. CNNs were particularly effective in identifying tumor regions based on texture and intensity variations within MRI images. However, their reliance on localized receptive fields limited their ability to capture long-range dependencies and global contextual relationships. This limitation became increasingly evident when dealing with complex tumor morphologies, irregular boundaries, and multi-class classification scenarios. Furthermore, CNN models often required extensive data preprocessing and augmentation to improve generalization, highlighting the need for more advanced architectures.

The year 2021 marked a pivotal turning point with the introduction of Transformer-based architectures into medical imaging. Vision Transformers (ViT) revolutionized image classification by treating images as sequences of patches and applying self-attention mechanisms to model relationships between different regions of the image. Unlike CNNs, which rely on hierarchical convolution operations, Transformers enabled direct modeling of global dependencies, resulting in significantly improved feature representation. Studies reported classification accuracies exceeding 97%, demonstrating the superiority of Transformer-based models over traditional CNNs. However, the high computational complexity and memory requirements of Transformers posed challenges, particularly for high-resolution MRI images. To address this issue, hybrid CNN-Transformer models were introduced, combining convolutional layers for local feature extraction with Transformer-based attention mechanisms for global context modeling. These hybrid architectures achieved improved accuracy and robustness while reducing computational overhead compared to pure Transformer models.

In 2022, research efforts focused on optimizing Transformer architectures for medical imaging applications. One of the most notable advancements was the introduction of axial attention mechanisms, which decompose multi-dimensional attention into separate spatial dimensions (height and width). This approach significantly reduces computational complexity while preserving the ability to capture global contextual information. Axial attention models demonstrated comparable performance to full self-attention models, achieving classification accuracies between 98% and 99%, while being more computationally efficient. Additionally, hierarchical Transformer models, such as Swin Transformer, introduced a multi-scale representation by processing images at different resolutions. This hierarchical design allowed models to capture both fine-grained details and coarse global features, resulting in improved classification performance. Transformer-based segmentation frameworks, including UNETR and TransBTS, further extended these capabilities by integrating attention mechanisms into encoder–decoder architectures, enabling simultaneous segmentation and classification of brain tumors.

By 2023, research had progressed toward more sophisticated architectures that emphasized efficiency, scalability, and integration of multiple attention mechanisms. Group parallel axial attention emerged as a significant advancement, enabling simultaneous processing of multiple attention heads across spatial dimensions. This approach improved computational efficiency and scalability, making it suitable for large-scale medical imaging datasets. Models incorporating group parallel attention achieved classification accuracies up to 99.4%, representing state-of-the-art performance. Additionally, hybrid models combining CNNs, Transformers, and attention mechanisms became increasingly prevalent. These models leveraged the strengths of different architectures to achieve superior performance in both classification and segmentation tasks. Multi-modal learning approaches also gained attention, integrating MRI data with other imaging modalities or clinical information to enhance diagnostic accuracy. Furthermore, explainable AI techniques, such as attention heatmaps and saliency maps, were incorporated to improve model interpretability and build trust among clinicians.

In 2024, the research landscape expanded to include emerging paradigms such as quantum self-attention, which integrates quantum computing principles into deep learning architectures. Quantum self-attention replaces classical matrix-based attention operations with parameterized quantum circuits, offering

potential advantages in computational efficiency and feature representation. Although still in the early stages of development, preliminary studies suggest that quantum-enhanced models can achieve classification accuracies up to 99.6%, surpassing traditional deep learning approaches in certain scenarios. This development represents a significant step toward next-generation AI systems capable of handling high-dimensional medical imaging data more efficiently.

Another important trend observed during this period is the increasing reliance on transfer learning and pre-trained models. Pre-trained Vision Transformers and hybrid architectures have been fine-tuned on medical datasets, enabling improved performance even with limited labeled data. This approach addresses the challenge of data scarcity, which is a common issue in medical imaging due to the high cost and expertise required for annotation. Additionally, data augmentation techniques and generative models, such as Generative Adversarial Networks (GANs), have been used to enhance dataset diversity and improve model robustness.

Despite these advancements, several challenges remain unresolved. Data imbalance and limited availability of annotated datasets continue to hinder model generalization and performance. Transformer-based models, while highly accurate, require substantial computational resources, making them difficult to deploy in real-time clinical environments. Interpretability remains a critical concern, as clinicians require transparent and explainable models to اعتماد AI-based decisions. Ethical considerations, including data privacy, bias, and fairness, also play a significant role in the adoption of AI systems in healthcare.

In summary, the literature from 2020 to 2024 demonstrates a clear progression from traditional CNN-based models to advanced Transformer and hybrid architectures, with increasing emphasis on efficiency, scalability, and interpretability. The integration of axial attention and group parallel mechanisms has addressed computational challenges, while hybrid models have achieved state-of-the-art performance. Emerging technologies such as quantum self-attention represent a promising future direction, with the potential to further revolutionize medical image analysis. Future research is expected to focus on developing lightweight, explainable, and clinically deployable models that can operate effectively in real-world healthcare environments.

Comparative Table and Analysis

Comparative Table

Year	Study/Author	Model & Key Techniques	Dataset(s) & Size	Reported Performance	Strengths	Limitations
2022	**Tummala et al. (Diagnostics)**	Vision Transformer ensemble (ViT-L/32, ViT-B/16, ViT-B/32) with majority voting	Figshare brain-tumour dataset (3 064 contrast-enhanced T1-weighted MRI slices of meningioma, glioma and pituitary tumours)	Single ViT-L/32 model achieved ~98.2 % accuracy at 384×384 resolution; ensemble accuracy ≈ 98.7 %	Captures global dependencies via self-attention; ensemble improves robustness	High computational and memory cost; requires large input resolution; limited interpretability
2024	**Ahmed et al. (Scientific Reports)**	Hybrid Vision Transformer–GRU model with explainable AI (Grad-CAM)	BrTMHD-2023 brain-tumour dataset; cross-validated; also evaluated on Kaggle brain-tumour dataset	Precision, recall and F1 all ~97 %; accuracy 81.66 % (SGD), 96.56 % (Adam), 98.97 % (AdamW) on BrTMHD-2023; ≈ 96.08 % accuracy on	Combines temporal modelling (GRU) with spatial attention; uses explainable AI heatmaps	Wide performance variance across optimisers; moderate dataset size; GRU adds training complexity

				the Kaggle dataset		
2024	**Benzorgat et al. (PeerJ Computer Science)**	Ensemble of CNNs (DenseNet201, GoogLeNet/InceptionV3, Inception-ResNet V2) followed by a transformer encoder using shifted-window self-attention (Swin transformer block)	Three public brain-tumour datasets: Cheng; BT-large-2c; BT-large-4c	Classification accuracy 99.34 % (Cheng), 99.16 % (BT-large-2c) and 98.62 % (BT-large-4c)	Hybrid architecture leverages CNN feature extraction and Transformer global context; shifted-window self-attention reduces complexity	Ensemble increases training time; may overfit small datasets; performance depends on dataset quality
2024	**Exploration of Medicine survey (comparative analysis)**	Comparison of multiple transformer families (ViT, DeiT, Swin, CaiT, T2T); emphasis on Swin Transformer's hierarchical architecture	Multiple brain-tumour MRI datasets (not specified); evaluation of small and large model variants	All models achieved > 98.8 % accuracy; Swin-Small and Swin-Large reached ~99.37 % accuracy with inference times of 0.54 ms and 1.29 ms, respectively	Demonstrates state-of-the-art performance; Swin models achieve high accuracy with reduced inference time; hierarchical representation captures multi-scale features	Focuses on classification accuracy; lacks detailed analysis of generalisation across institutions; hardware requirements not reported
2023	**Demiroğlu (Adıyaman Univ. J. Science)**	Axial Attention CNN (Axial-CNN); attention decomposed along height and width axes	Brain MRI datasets (details not specified)	Reported that axial attention reduces computational complexity while capturing long-term dependencies	Efficient for high-resolution images; improves context modelling with lower memory footprint	Lacks quantitative accuracy comparisons; developed primarily as a conceptual demonstration
2024	**Quantum self-attention (conceptual studies)**	Quantum self-attention models using parameterised quantum circuits for attention operations	Simulated brain-tumour datasets; early proofs of concept	Preliminary results report classification accuracies up to ~99.6 % (model-dependent)	Potential to reduce classical computational complexity and represent high-dimensional	Still theoretical; limited by current quantum hardware; reproducibility remains uncertain

					features more efficiently	

Analysis

The comparative evaluation across brain-MRI classification studies demonstrates a clear progression from conventional convolutional models to sophisticated Transformer-based and hybrid architectures. Early CNN-based approaches, though effective at capturing local texture variations, struggled to model long-range dependencies and often achieved accuracies below 95 %. These limitations motivated the adoption of Vision Transformers, which employ self-attention to relate distant image patches. Tummala et al. showed that a single ViT model achieved roughly 98.2 % accuracy on a 3 064-slice dataset, and an ensemble of ViTs increased accuracy to about 98.7 %. Such results highlight the strength of self-attention in capturing global context but also underscore the high computational cost associated with processing high-resolution MRI slices.

Hybrid models emerged to balance accuracy and efficiency. Ahmed et al. combined a Vision Transformer with a gated recurrent unit (GRU) and employed explainable AI techniques to visualise salient regions. Their hybrid model achieved F1, precision and recall scores around 97 % and reached nearly 99 % accuracy when trained with the AdamW optimiser. The integration of GRU enabled temporal modelling of patch embeddings, while the ViT component captured spatial relationships. However, the performance varied notably with the choice of optimiser, suggesting that optimisation and training stability remain key issues.

Another strategy to improve classification involves blending multiple CNN architectures with Transformer encoders. Benzorgat et al. constructed an ensemble of DenseNet201, GoogleNet and Inception-ResNet V2, feeding their combined features to a Swin Transformer encoder that uses shifted-window self-attention. This architecture achieved state-of-the-art accuracies of 99.34 % on the Cheng dataset and > 98.6 % on other datasets. By leveraging CNNs to extract low-level features and a Transformer block for global context, the model benefits from both paradigms. The shifted-window mechanism reduces the quadratic complexity of full attention, making the model more scalable. However, ensemble methods introduce training overhead and can be prone to overfitting when datasets are limited.

Comparative surveys, such as the one published in *Exploration of Medicine*, reinforce the dominance of Transformer families. The survey evaluated multiple models (ViT, DeiT, CaiT, Swin, etc.) and found that even the smallest Swin Transformer variant achieved accuracy around 99.37 % with sub-millisecond inference time. These results show that hierarchical Transformer architectures capture both fine and coarse features efficiently, making them attractive for clinical deployment. Furthermore, the survey noted that all examined Transformer models surpassed 98.8 % accuracy, underlining the maturity of attention-based approaches.

Axial attention models address the computational challenges of full self-attention by decomposing attention along spatial axes. Demiroğlu's work on Axial-CNN demonstrated that this decomposition reduces complexity without sacrificing the ability to model long-term dependencies. Although the study did not provide detailed accuracy benchmarks, axial attention has been integrated into larger architectures such as Swin Transformers, where it underpins the shifted-window mechanism. Group parallel axial attention extends this concept by processing multiple attention heads in parallel across spatial dimensions, enabling near-real-time inference—a critical requirement for clinical settings.

The most speculative yet promising direction is quantum self-attention. By implementing attention operations on quantum hardware, these models aim to exploit quantum parallelism to process high-dimensional data more efficiently. Early simulations suggest that quantum attention could achieve accuracies up to 99.6 % on brain-tumour classification tasks, marginally exceeding classical counterparts. However, practical quantum computing remains in its infancy, and such models currently rely on simulators rather than real quantum processors. Therefore, while quantum attention offers a compelling future trajectory, its clinical impact will depend on advances in quantum hardware and algorithm design.

Overall, the comparative analysis highlights a trajectory from CNNs to Transformers, hybrid models and beyond. Transformer-based models deliver remarkable accuracy and are now the de-facto standard for brain-MRI classification. Axial and group-parallel attention mechanisms mitigate the computational burden of self-attention, enabling efficient analysis of high-resolution images. Hybrid architectures achieve a favourable balance between accuracy and efficiency, while emerging quantum approaches hint at further gains. Future work

should focus on constructing lightweight, interpretable and generalisable models that can be deployed across diverse clinical environments, address data scarcity through transfer learning and augmentation, and integrate multi-modal information to enhance diagnostic precision.

Discussion

The rapid advancements in deep learning have significantly transformed brain MRI classification, particularly with the adoption of Transformer-based architectures. These models have demonstrated superior performance by effectively capturing global contextual relationships, which are essential for accurate tumor classification. Unlike traditional CNNs, Transformers utilize self-attention mechanisms to analyze the entire image, enabling improved feature representation and classification accuracy.

Axial attention mechanisms have further enhanced the efficiency of Transformer models by reducing computational complexity. This advancement is particularly important for medical imaging applications, where high-resolution data requires significant computational resources. By decomposing attention into spatial dimensions, axial attention enables efficient processing without compromising performance.

Hybrid CNN-Transformer models represent a balanced approach, combining the strengths of both architectures. These models achieve high accuracy while maintaining computational efficiency, making them suitable for clinical applications. Additionally, group parallel attention mechanisms improve scalability, enabling real-time analysis of medical images.

Quantum self-attention introduces a novel paradigm by integrating quantum computing principles into deep learning. Although still in early stages, these models have the potential to revolutionize medical image analysis by improving computational efficiency and feature representation.

Despite these advancements, challenges remain. Data scarcity is a major limitation, as medical datasets require expert annotation. Computational complexity is another concern, particularly for Transformer-based models. Interpretability is also critical, as clinicians require transparent and explainable models. Future research should focus on lightweight architectures, explainable AI, and multi-modal data integration.

Conclusion

This systematic review highlights the rapid evolution of brain MRI classification techniques, driven by advancements in Transformer-based architectures, axial attention mechanisms, and quantum self-attention models. The findings demonstrate a clear transition from traditional CNN-based approaches to more advanced attention-based and hybrid models.

Vision Transformers have significantly improved classification accuracy by capturing global dependencies, while axial attention mechanisms have addressed computational challenges. Hybrid models have emerged as the most effective approach, combining accuracy and efficiency. Group parallel attention has further enhanced scalability, enabling real-time analysis. Quantum self-attention represents a promising future direction, offering potential advantages in computational efficiency and feature representation. However, challenges such as data scarcity, computational complexity, and interpretability remain.

Future research should focus on developing lightweight and explainable models, integrating multi-modal data, and exploring quantum computing techniques. These advancements will contribute to the development of reliable and efficient diagnostic systems, ultimately improving patient outcomes.

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