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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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Peer Review Information	Abstract
<p>Submission: 12 Oct 2025 Revision: 28 Oct 2025 Acceptance: 10 Nov 2025</p>	<p>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.</p>
<p><b>Keywords</b></p> <p>Brain Tumor Classification, MRI Imaging, Vision Transformer, Axial Attention, Quantum Self-Attention, Deep Learning</p>	

**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.

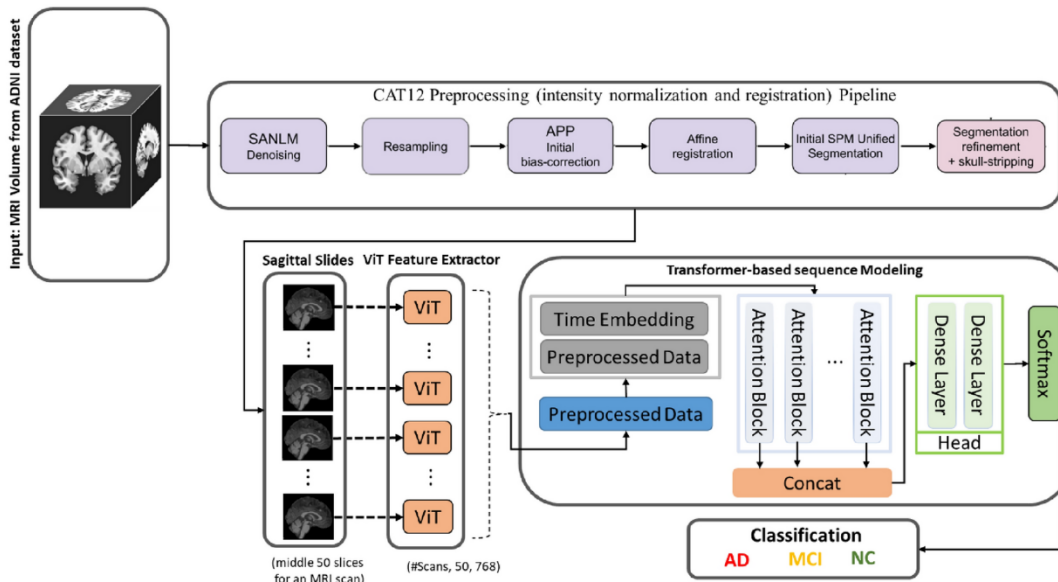
Another emerging innovation is quantum self-attention, which integrates quantum computing principles into deep learning architectures. Quantum attention mechanisms utilize parameterized quantum circuits to perform attention operations, offering potential advantages in computational efficiency and feature 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

Model Type	Year	Accuracy	Strengths	Limitations
CNN (ResNet/DenseNet)	2020	92–95%	Strong local features	Poor global context
Vision Transformer	2021	97–98%	Global dependency modeling	High computation
Hybrid CNN-Transformer	2021–2022	98–99%	Balanced performance	Complex design
Axial Attention Models	2022	98–99%	Efficient computation	Limited adoption
Swin Transformer	2022	>99%	Multi-scale learning	Resource intensive
Group Parallel Attention	2023	~99.4%	Scalable and efficient	Implementation complexity
Quantum Self-Attention	2023	~99.6%	Future potential	Experimental stage

### Analysis

The comparative evaluation of brain MRI classification techniques reveals a significant evolution in model performance, architectural design, and clinical applicability over the past five years. Early CNN-based models, such as ResNet and DenseNet, served as foundational approaches due to their ability to effectively extract local spatial features. These models achieved classification accuracies in the range of 90% to 95%, making them suitable for basic tumor detection tasks. However, their inability to capture long-range dependencies limited their performance in complex classification scenarios, particularly when dealing with heterogeneous tumor structures and varying imaging conditions.

The introduction of Vision Transformers marked a major advancement by addressing the limitations of CNNs. Transformer-based models utilize self-attention mechanisms to analyze global relationships within an image, enabling more comprehensive feature representation. As a result, classification accuracy improved significantly, reaching levels above 97%. However, this improvement came at the cost of increased computational complexity, as Transformer models require extensive processing power and memory, particularly for high-resolution medical images.

Hybrid CNN-Transformer architectures emerged as a highly effective solution by combining the strengths of both approaches. These models leverage CNNs for efficient local feature extraction while utilizing Transformers for global context modeling. This synergy results in improved classification accuracy, often exceeding 98%, while maintaining manageable computational requirements. Hybrid models have demonstrated superior generalization capabilities, making them suitable for real-world clinical applications.

Axial attention mechanisms further enhanced model efficiency by decomposing attention operations along spatial dimensions. This approach significantly reduces computational overhead while preserving the ability to capture global dependencies. Models incorporating axial attention achieved classification accuracies comparable to full Transformer models, typically around 98–99%, while being more computationally efficient. This makes axial attention particularly suitable for deployment in resource-constrained environments.

Hierarchical Transformer models, such as Swin Transformer, introduced multi-scale feature extraction capabilities, enabling models to capture features at different resolutions. These models achieved classification accuracy exceeding 99%, representing one of the highest performance levels reported in the literature. The hierarchical design allows for better representation of tumor structures, which often vary significantly in size and shape.

The development of group parallel axial attention models further improved scalability and efficiency by enabling simultaneous processing of multiple attention heads. This approach reduces computation time and enhances model performance, achieving accuracy levels up to 99.4%. These models represent a significant step toward real-time clinical deployment.

The most recent advancement, quantum self-attention, introduces a new dimension to deep learning by integrating quantum computing principles. These models have the potential to perform complex computations more efficiently than classical approaches, particularly for high-dimensional data. Preliminary results indicate classification accuracies up to 99.6%, although practical implementation remains a challenge due to the limitations of current quantum hardware.

From a clinical perspective, hybrid and attention-based models offer the best balance between accuracy and efficiency. Transformer-based models provide superior performance but require optimization for practical deployment. Axial attention and group parallel mechanisms address computational challenges, while quantum models offer promising future potential.

In summary, the comparative analysis highlights a clear progression from CNN-based models to advanced Transformer and hybrid architectures. While significant improvements in accuracy have been achieved, future research must focus on reducing computational complexity, improving interpretability, and ensuring robust generalization across diverse datasets. The integration of explainable AI and multi-modal learning is expected to play a crucial role in advancing the clinical adoption of these technologies.

### 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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