EAI Endorsed Transactions
on e-Learning

Research Article **EAI.EU**

A Review of Deep Learning Methods for Brain Tumor Detection

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Abstract

A brain tumor is a serious neurological condition caused by the growth of abnormal cells in various regions of the brain, leading to a variety of health issues. Although the specific causes of brain tumors are not yet fully understood, known risk factors include genetic predisposition, ionizing radiation, viral infections, and exposure to certain chemicals. With the advancement of deep learning technology, computer-aided diagnosis systems can offer crucial support for the early diagnosis of brain tumors. Brain tumor image classification using deep learning has emerged as a prominent area of research. This article begins by summarizing the publicly available datasets frequently utilized in brain tumor classification tasks. It then provides an overview of the models commonly applied for diagnosing brain tumors. Following this, the paper reviews the advancements made in the field of brain tumor classification research to date. Finally, it highlights the future trends and challenges in brain tumor classification.

Keywords: Deep learning, Disease Diagnosis, Brain Tumour, Medical Image

Received on 15 01 2025, accepted on 06 02 2025, published on 07 02 2025

doi: 10.4108/eetel.8441

1. Introduction

This Brain tumors result from abnormal cell growth in brain tissue or nearby structures, potentially causing increased intracranial pressure, neurological issues, and impairments in cognitive and motor functions, which can severely affect a patient's health and quality of life [1]. Currently, diagnosis typically involves using imaging technologies such as computed tomography (CT), magnetic resonance imaging (MRI), positron emission tomography (PET), and single-photon emission computed tomography (SPECT) to scan the brain. Physicians then combine these results with their expertise to assess the tumor's location, size, and condition to develop an appropriate treatment plan [2]. However, diagnostic accuracy can vary depending on the clinician's expertise and the quality of the imaging equipment, raising the risk of misdiagnosis. To address this, advanced computer-aided diagnosis algorithms have been developed to enhance diagnostic precision.

In recent years, deep learning-based approaches for brain tumor diagnosis have yielded impressive results.[3] Unlike traditional machine learning techniques that rely on manually designed features, deep learning methods utilize neural networks to automatically extract high-level features from large datasets of brain tumor images [4]. These methods employ various optimization algorithms, such as network modules that capture both global and local context features [5], as well as multi-scale feature fusion techniques [6], to refine the extracted features and achieve highly accurate brain tumor diagnoses. In computer-aided diagnostic systems that utilize deep learning, classification models are particularly prominent. Current methods in brain tumor image diagnosis include convolutional neural networks (CNN) [7], [8], visual transformers (ViT) [9], graph neural networks (GNN) [10], and other models.

In this article, we first conduct a statistical analysis of several datasets commonly used in brain tumor classification research. Next, we explore several widely used classification methods in brain tumor research, delving into their respective strengths and limitations. Lastly, we address the challenges of

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using deep learning to assist in brain tumor diagnosis and outline potential future research directions.

2. Datasets

2.1. Figshare Brain Tumor Dataset

Cheng et al. [11] introduced a widely utilized dataset for brain tumor classification research, available on Figshare (https://figshare.com/articles/dataset/brain_tumor_dataset/1512427). This dataset comprises 3,064 T1-weighted enhancedimages from 233 patients, categorized into three types: meningioma, glioma, and pituitary tumor. It includes 708 meningioma images, 1,426 glioma images, and 930 pituitary tumor images, with each sample documenting the discrete point coordinate vector of the tumor boundary. The images are provided in three views—axial, coronal, and sagittal—and are stored in Matlab (.mat) format. Additionally, the dataset offers a 5-fold cross-validation index for model evaluation and validation.

2.2. BraTS Challenge Dataset

The BraTS dataset(http://braintumorsegmentation.org/) is a comprehensive multimodal brain tumor dataset originating from the BraTS challenge, which has been held annually since 2012. Over time, the dataset has grown significantly, reaching 8,160 MRI scans from 2,040 patients by 2021. Although BraTS2022 and BraTS2023 have been released, they only include additional test data. Each patient's dataset comprises MRI images in four modalities: T1, T1Gd, T2, and T2-FLAIR. Of these, 1,251 cases are annotated and used as the training set, 219 cases form the validation set, and 570 cases constitute the test set. The images were collected from various medical facilities, employing diverse clinical protocols and scanning equipment. Annotations in BraTS21 focus on three regions: enhancing tumor (ET), peritumoral edema or invasive tissue (ED), and necrotic tumor core (NCR). While primarily designed for brain tumor segmentation, the BraTS dataset's scale and credibility have also made it a favored resource for evaluating brain tumor classification methods [12], [13].

2.3. Kaggle Brain Tumor Dataset

KBTD (Kaggle Brain Tumor Dataset)[14] is a competition dataset from the Kaggle platform(https://www.kaggle.com/datasets/masoudnickparvar/brain-tumor-mri-dataset), containing 3264 samples, covering four types of brain MR scan images: glioma, meningioma, pituitary tumor, and normal brain images. These brain tumor images come from different patients, including a combination of three types: T1, T2, andFLAIR. The image sizes in the dataset vary, with the largest image size being 1375×1446 and the smallest image size being 175×167. Due to the difference in image size, preprocessing is required when using this dataset, which poses a considerable challenge to the brain tumor classification task.

3. Research progress in brain tumor diagnosis

3.1. Convolutional Neural Networks

3.1.1. Brief Introduction of Convolutional Neural Network

Convolutional Neural Networks (CNNs) are deep learning models specifically designed for processing grid-like data, such as images. They are widely applied in fields like image recognition [15] and natural language processing [16]. A typical CNN structure includes convolutional layers, pooling layers, and fully connected layers. These networks perform hierarchical feature extraction and nonlinear transformations, enabling the automatic learning of meaningful features from raw input [17]. Convolutional layers utilize small filters that traverse the input to capture local features while maintaining spatial relationships. Pooling layers reduce dimensionality through downsampling, which improves the model's generalization capabilities by lowering the number of parameters. Fully connected layers integrate the extracted features to generate the final classification result. As depicted in Figure 1, a CNN designed for brain tumor image analysis starts with an input layer, followed by convolutional and pooling layers, a fully connected layer, and a SoftMax output layer.

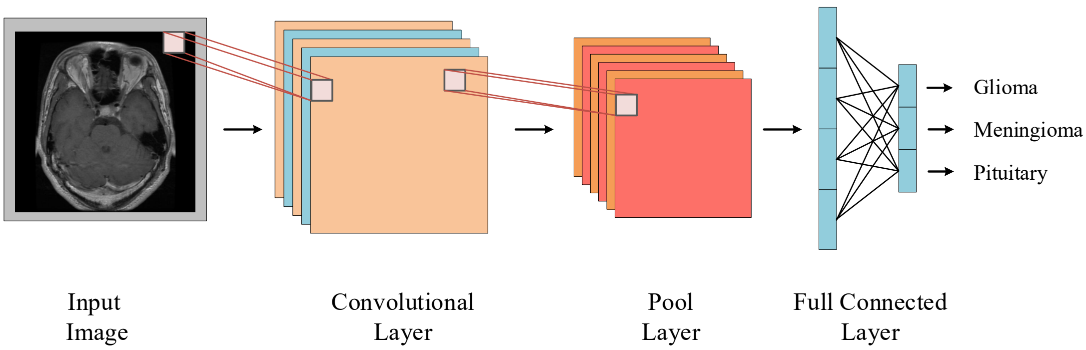

Figure 1. Classic CNN framework diagram

3.1.2. Convolutional Neural Networks for Brain Tumor Diagnosis

CNNs for brain tumor diagnosis are often used to classify 2D brain tumor images. These 2D images are often 2D slices based on sagittal, cross-sectional, and coronal scans of 3D brain tumor images. By collecting a large number of 2D brain tumor slices, CNNs can capture complete tumor descriptions and achieve high-precision diagnosis.

Numerous studies have demonstrated that deep learning approaches for diagnosing brain tumors frequently outperform traditional machine learning techniques. Saeedi et al. [18] conducted a comparison between various conventional machine learning algorithms, including KNN, SVM, logistic regression, random forest, and others, against deep learning models. In their study, the KNN algorithm reached an accuracy of 86% on the KBDT dataset, marking its top performance among the traditional methods, yet it fell short compared to the 96.47% accuracy attained by the convolutional neural network. However, when the existing CNN model is combined with a relatively mature classifier, the model prediction effect will be improved [19]. To this end, Sejuti et al. [20] proposed a 19-layer CNN-SVM model, which is a combination of a classic CNN network and a machine-learning SVM.This model comprises a 2D convolutional layer, a pooling layer, and a fully connected layer. What sets this study apart is its use of SVM to refine the features extracted by the model, thereby enhancing the CNN's accuracy. Likewise, Srinivas et al. [21] introduced a CNN-KNN hybrid framework, utilizing CNN for feature extraction and KNN for making predictions, achieving an accuracy of 96.25% on the BraTS2017 test dataset.

The above two studies both adopted the classic CNN network architecture. However, they are both shallow neural networks and their capabilities are relatively limited when dealing with complex feature extraction and high-precision classification tasks. Deeper neural networks have significant advantages when handling complex tasks. Srinivas et al. [22] used the pre-trained GoogLeNet [23] to extract features from brain MRI images. This is a deeper network and then used the KNN algorithm to classify the extracted features. Ultimately, the 5-fold cross-validation technique was applied, resulting in an average accuracy of 98% on the Figshare dataset. This also underscores the efficacy of combining transfer learning approaches with deep neural networks.

Unlike the single-branch structure used in the above literature, Al-Zoghby et al. [24] proposed a convolutional network with two backbone branches, one branch using the VGG-16 network and the other branch using a custom CNN network. The features obtained from the two branches were subsequently combined for classification. Masoudi et al. [25] used ResNet50 as the backbone network to extract features, and used a two-branch structure at the end of the network, using channel attention and multi-head attention to fuse features. Unfortunately, this multi-branch network model often has a large number of parameters and requires a lot of time to train.

To mitigate the issue of extended training time, Isunuri et al. [26] used deep separable convolution to construct a network, effectively reducing the number of convolution parameters by performing deep convolution on each channel independently. At the same time, they proposed a neural network with only 7 layers to classify brain tumor images and used the Nadam optimizer [27] to speed up the convergence of the diagnosis model.

The aforementioned analysis highlights that employing convolutional neural network techniques for brain tumor diagnosis possesses the following traits: (1) The integration of deep learning with machine learning typically yields superior results compared to using one in isolation. (2) The abundance of detailed brain information contained within numerous MRI images facilitates the development of more complex network architectures, enabling highly accurate recognition and diagnostic capabilities. (3) Using transfer learning models as initialization or feature extractors can greatly accelerate the convergence of the model and improve the effectiveness of network terminal training and learning [28], [29].

However, the CNN method also has the following problems that need to be solved: (1) Although the model accuracy can be improved to a certain extent by building a deeper neural network, the cost is generally much greater than the benefits obtained. (2) Due to the complexity of brain tumor MRI neuroimaging, the use of transfer learning to initialize the network model can reduce the difficulty of model training, but in the actual application of brain tumor classification diagnosis, the real target type discrimination results are not stable. (3) Although deep separable convolution can greatly reduce model parameters and increase model training speed, this may sacrifice the model's diagnostic results. Therefore, researchers must find a reasonable balance between reducing model complexity and maintaining diagnostic accuracy.

3.2. Transformer

3.2.1. Brief Introduction of Transformer

The Transformer [30], an encoder-decoder architecture grounded in self-attention mechanisms, was initially introduced to address sequence-to-sequence (seq2seq) tasks within natural language processing [31]. When compared to traditional recurrent neural networks (RNNs) and long short-term memory networks (LSTMs), the Transformer offers distinct advantages. Transformer has significant advantages in handling long dependencies and parallel computing. The original Transformer cannot perform computer vision tasks. In 2020, the Google group proposed ViT [9]. This research first proved that Transformer has great potential in the field of computer vision. The ViT framework is shown in Figure 2. In the Transformer-based brain tumor diagnosis task, the input image first needs to be segmented into a series of non-overlapping patches, then position coding information is added to these patches to retain spatial information, and a class token is added to the starting position of the patch sequence. Finally, this special token is input into the Transformer encoder together with all other patches for subsequent classification tasks.

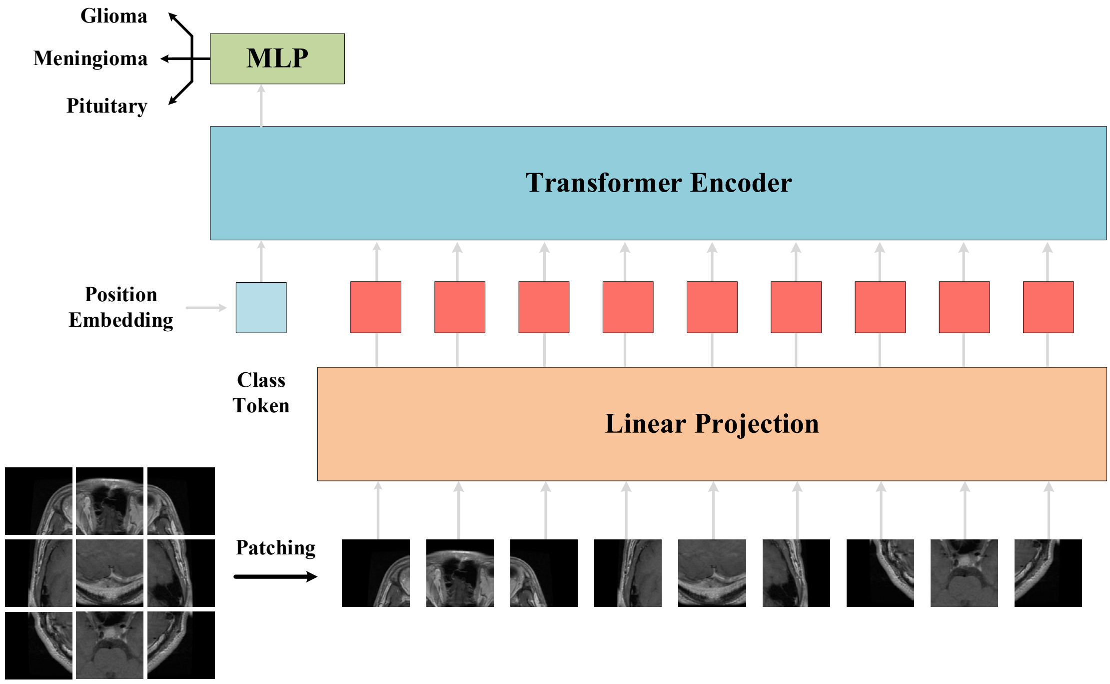

Figure 2. ViT for brain tumor classification framework

3.2.2. Transformer for Brain Tumor Diagnosis

While convolution operations excel at capturing local features, they are less effective at extracting global features and maintaining long-distance dependencies, a limitation that the Transformer addresses. Tummala et al. [32] evaluated the ViT model's capability to classify brain tumor images from T1W, CE, and MRI scans. Their findings indicated that, at high resolutions, the ViT model's performance can match or surpass that of earlier CNNs.

The effectiveness of the ViT model depends on two key factors: (1) It requires a large training dataset to achieve optimal performance. With limited data, most Transformer variants often underperform compared to the VGG-16 baseline [33]. (2) The self-attention mechanism in ViT leads to quadratic computational complexity relative to the length of the image's patch sequence. While the Swin Transformer [34] addresses this by reducing attention calculation costs to linear through moving window-based attention between layers, the challenge of high-performance Transformers needing extensive data remains unresolved. To tackle this, Ferdous et al. [35] introduced a data-efficient image transformer (LCDEiT) with linear complexity for brain tumor diagnosis. This approach utilized a gated pooling CNN as a teacher model to transfer knowledge to a Transformer-based student model, reducing reliance on large datasets.

Research shows that Transformers excel at capturing global information, whereas CNNs are more adept at extracting local features. Combining these models can yield superior results. Aloraini et al. [36] proposed enhancing CNNs with Transformers by incorporating feature fusion modules and intelligent merging modules (IMM) to bridge the semantic gap between Transformer and CNN feature maps, achieving a 96.75% accuracy on the BraTS2018 dataset. Similarly, Tabatabaei et al. [37] developed a dual-branch parallel model that integrates Transformer and CNN modules, using a cross-fusion strategy to combine deep features for classification, with results surpassing individual models. Further, Dutta et al. [38] introduced a generalized self-attention module (GSB) to capture feature interdependencies across spatial and channel dimensions effectively.

Although the combination of the Transformer and CNN can achieve satisfactory performance in brain tumor diagnosis tasks, the training and fine-tuning of the Transformer requires a lot of time and memory. Wang et al. [39] calculated similar tokens in the image based on the binary soft matching algorithm and merged them, gradually reducing the token length, and finally reducing the model calculation time. Gade et al. [40] started from the three self-attention matrices, merged W_q， W_k and W_v into one, and reduced the theoretical time complexity to O(N^2/2)by eliminating the matrix Q and the matrix K. However, due to the high complexity of Transformer, CNN will still maintain its leading position for some time with its reasonable number of parameters [41].

3.3. Graph Neural Networks

3.3.1. Brief Introduction to Graph Neural Networks

Graph neural networks (GNNs) utilize graph structures to handle data with intricate relationships. As depicted in Figure

3, nodes represent entities, and edges signify the relationships between these entities. CNN and Transformer can only process regular Euclidean data, however, GNN can process complex non-Euclidean data by modeling irregular data with graphs. GCN [10] is a typical representative of graph neural networks. Similar to the convolution process of CNN, GCN implements graph convolution through a message-passing mechanism, that is, attribute updates and information interaction of key nodes. Nowadays, GCN has given rise to several variants, including graph attention networks [42] and graph residual networks. Among them, graph attention networks convolute and assign weights to each adjacent node to identify important nodes. Graph residual networks use skip connections to solve the problem that graph convolution layers with more than 3 layers will introduce noise, resulting in poor results. GNN has found widespread application in the field of medical imaging [43], [44].

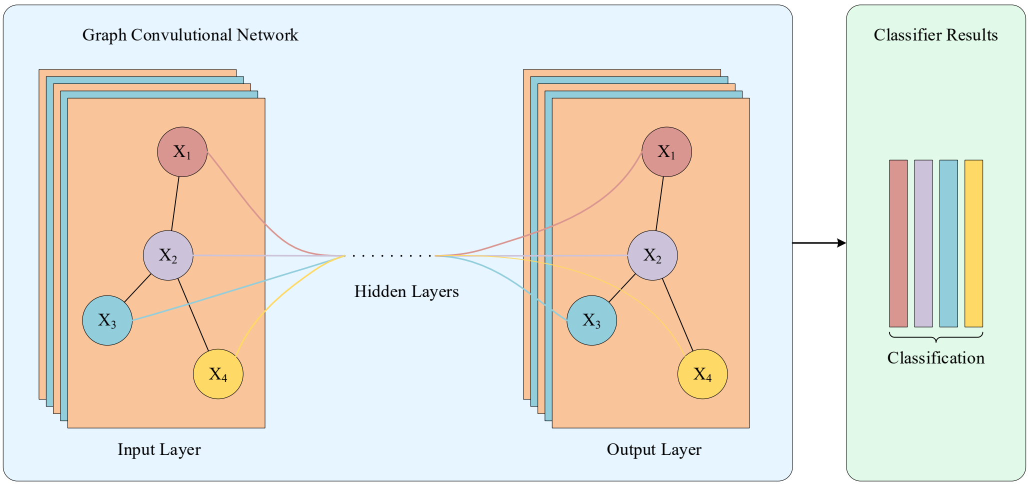

Figure 3. The framework of Graph Convolutional Network

3.3.2. Graph Neural Networks for Brain Tumor Diagnosis

Ravinder et al. [45] observed that in MRI images, nearby pixels often share similar attributes, whereas distant pixels tend to differ significantly. Traditional brain tumor classification models, however, struggle to leverage pixel-related information effectively. To address this, they combined CNN and GNN for classification, with CNN capturing spatial features and GNN identifying dependencies between image regions [46]. Their experiments demonstrated that integrating these models enhances performance. Similarly, Mishra et al. [47] proposed a framework combining a graph attention encoder [48] with CNN for brain tumor diagnosis. The graph attention encoder improves the visual quality of tumor images, which are subsequently classified by CNN. To streamline the training process, the Adamax optimizer was employed. However, the framework's reliance on unsupervised learning demands significant computational resources.

While GNN excels at handling complex data relationships compared to CNN, it also has limitations, including the over-smoothing issue [49]. As the number of GNN layers increases, the node feature vectors become overly uniform after deep graph convolution, resulting in a sharp performance decline. This significantly hampers GCN's ability to represent large-scale graphs [50], adversely affecting brain tumor diagnosis. For instance, Liu et al. [51] limited the number of GCN layers to two in their study on glioma diagnosis to prevent over-smoothing and preserve performance.

To alleviate the over-smoothing problem of GNN, researchers have introduced various techniques such as DropEdge[52], skip connections, node normalization, and dilation aggregation into GNN. For example, Tang et al. [53] proposed the MRCG framework by randomly deleting edges in the graph through the DropEdge method, which greatly reduced the convergence speed of GNN transition smoothing. The final experimental results of the proposed model outperformed all baseline models. Liu et al. [54] used a node normalization layer to prevent all node embeddings from converging to the same, thereby improving the robustness of GNN in dealing with the over-smoothing problem and alleviating the overfitting problem.

Among the strategies to address the over-smoothing problem in GNNs, skip connections are among the simplest and most commonly used. These connections involve directly adding the original input or the output of a lower layer to a higher layer's output, helping to retain original feature information and reduce information loss caused by excessive aggregation [55]. Salim et al. [56] proposed an aggregator-normalized graph convolutional network that leverages graph sampling, skip connections, and identity mapping to learn distinctive node representations. Skip connections facilitate the direct transfer of input features to subsequent layers, mitigating over-smoothing in GCNs. Meanwhile, identity mapping aids in preserving the graph's structural information during feature learning.

4. Challenges and Prospects

4.1. Challenges

Brain tumors are a significant global health concern, making early diagnosis and detection crucial. This article examines the role of deep learning in brain tumor diagnosis and highlights recent advancements in the field. While deep learning has become essential for early detection, several challenges remain to be addressed:

(1) Acquiring datasets is a major challenge in medical image analysis. Medical images require expensive specialized equipment like X-rays, CT scanners, and MRIs to produce, making it especially difficult to obtain high-quality data. In addition, medical image data often contains a large amount of sensitive patient privacy information, and its collection, storage, and use are subject to strict legal and regulatory requirements [57]. These factors together increase the difficulty of obtaining and sharing high-quality medical image data.

(2) The lack of model interpretability is an urgent problem that needs to be solved. In the medical field, doctors and researchers not only need accurate prediction results but also need to understand the basis for the model to make a specific diagnosis[58]. Present deep learning models, particularly complex neural networks, are frequently viewed as "black box" models, whose internal operating mechanisms are opaque and difficult to understand. This lack of interpretability limits the application of models in clinical practice.

(3) The gap between technology and clinical practice is an issue that cannot be ignored. Current medical systems and operating procedures are often not fully considered when they are designed, so there are many challenges in the actual deployment of technology [59]. In addition, the stability and safety of technology are key considerations in clinical applications, and any technical errors may cause serious patient safety risks. This means that the application of new technologies requires not only advancement but also reliability and safety in actual operations.

4.2. Prospects

Brain tumor classification methods based on deep learning can extract deep features from complex medical imaging data and provide doctors with accurate tumor grading and type judgment. Detecting brain tumors at an early stage and correctly classifying them through fast and cost-effective diagnostic technology can potentially save many lives. Looking ahead, brain tumor classification methods based on deep learning will be further developed in the following directions:

(1) Classification algorithms based on 3D brain tumor scan images have great potential. Future brain tumor classification methods will rely more on three-dimensional (3D) imaging data rather than traditional two-dimensional images. Three-dimensional scans, such as MRI and CT scans, provide more comprehensive tumor morphology and spatial information, enabling the model to more accurately identify the boundaries and size of the tumor, thereby improving the accuracy of classification [60]. However, the computational complexity of processing 3D data is high, and more efficient algorithms and computing frameworks need to be developed to achieve real-time and accurate clinical applications.

(2) Expand the training dataset through data augmentation and synthesis. Given the challenges in acquiring high-quality medical imaging data, data scarcity remains a significant bottleneck for training deep learning models. Utilizing techniques like generative adversarial networks (GANs) can help generate realistic synthetic images, expand the dataset, and enhance the model's generalization capability [61]. Additionally, data augmentation methods, including random rotation, scaling, and cropping, can boost data diversity and minimize the risk of overfitting. Moving forward, effectively generating synthetic data that aligns with the distribution of real data and ensuring its quality will be crucial for optimizing data-driven medical models.

(3) Multimodal learning and cross-domain knowledge transfer: Brain tumor diagnosis typically involves integrating various types of medical images and data, such as MRI [62], CT [63], and pathology reports. Multimodal learning can combine features from different sources to offer a more complete tumor representation, thus enhancing classification accuracy and robustness. Moreover, cross-domain knowledge transfer can aid in addressing data scarcity by leveraging existing knowledge from related fields or similar tasks, such as using imaging data from other tumor types or scan data from other body regions to boost the performance of brain tumor classification models [64]. Looking ahead, the integration of multimodal and cross-domain learning is expected to substantially improve the effectiveness and clinical utility of brain tumor classification methods.

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