ONLINE ISSN :3007-309X
PRINT ISSN :3007-3081

Journal of Medical & Health Sciences Review

A SELF-SUPERVISED LEARNING MODEL FOR THE CLASSIFICATION OF BRAIN TUMORS USING MEDICAL IMAGES: A REVIEW

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ARTICLE INFO

Keywords: Self-Supervised Learning (SSL), Brain Tumor Classification,Medical Imaging,Deep Learning (DL),Contrastive Learning,Generative Models,Unlabeled Data,MRI (Magnetic Resonance Imaging),Federated Learning,Convolutional Neural Networks (CNNs).

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ABSTRACT

Brain tumors are critical neurological disorders, and early detection is essential for effective treatment. Traditional diagnostic methods, which rely on manual interpretation of medical images, are time-consuming, error-prone, and dependent on clinician expertise. With advancements in artificial intelligence (AI) and deep learning (DL), there has been significant progress in automating the detection and classification of brain tumors from medical images. However, a significant challenge remains: the limited availability of large, annotated datasets. Annotated data is expensive, scarce, and often subject to privacy concerns, making it difficult to fully leverage deep learning techniques. To address this issue, self-supervised learning (SSL) has emerged as a promising solution. SSL enables deep learning models to generate supervisory signals from unlabeled data, significantly reducing the need for manual annotation. This is particularly beneficial in medical imaging, where acquiring labeled data can be costly and time-consuming. SSL methods, such as contrastive learning, rotation prediction, and jigsaw puzzles, allow models to learn meaningful feature representations from unlabeled data, which can then be fine-tuned for tasks like tumor classification. Techniques like contrastive learning (e.g., SimCLR, MoCo, and BYOL), generative models (e.g., autoencoders and GANs), and clustering-based approaches (e.g., DeepCluster and SwAV) have shown success in learning from unlabeled medical images. In addition, SSL facilitates the integration of multiple imaging modalities, such as MRI, CT, and PET scans. By combining these modalities, SSL models can leverage complementary information, leading to enhanced tumor classification accuracy and robustness. Federated learning (FL) combined with SSL allows for collaborative model training across multiple institutions without sharing sensitive patient data, thus ensuring privacy. Despite the significant advancements in SSL for brain tumor classification, challenges remain. These include the need for small labeled datasets for fine-tuning, domain shifts across imaging modalities, interpretability issues, and the computational complexity of training deep SSL models. In conclusion, SSL has the potential to revolutionize brain tumor classification by reducing the reliance on large annotated datasets. Continued research into SSL techniques can lead to more accurate and efficient diagnostic tools, improving patient outcomes through earlier and more precise tumor detection.

Abbreviations:

1. AI - Artificial Intelligence
2. BYOL - Bootstrap Your Own Latent
3. CNN - Convolutional Neural Network
4. CT - Computed Tomography
5. DL - Deep Learning
6. FL - Federated Learning
7. GAN - Generative Adversarial Network

8. Grad-CAM - Gradient-weighted Class Activation Mapping
9. ICCV - IEEE/CVF International Conference on Computer Vision
10. MICCAI - Medical Image Computing and Computer-Assisted Intervention
11. MoCo - Momentum Contrast
12. MRI - Magnetic Resonance Imaging
13. PET - Positron Emission Tomography
14. RSNA - Radiological Society of North America
15. SimCLR - Simple Contrastive Learning of Representations
16. SSL - Self-Supervised Learning
17. SwAV - Swapping Assignments between Views
18. VAE - Variational Autoencoder
19. XAI - Explainable AI

1. Introduction

Brain tumors are one of the leading causes of death and disability worldwide, representing a critical challenge in the field of neuro-oncology. Early and accurate diagnosis is crucial for effective treatment planning, prognosis prediction, and decision-making regarding surgical interventions or radiotherapy. Tumor classification plays a pivotal role in determining the appropriate course of treatment, as different tumor types and grades have vastly different clinical implications. Historically, the diagnosis and classification of brain tumors have relied heavily on the expertise of clinicians who manually analyze medical imaging data, such as magnetic resonance imaging (MRI), computed tomography (CT), and positron emission tomography (PET) scans. These imaging modalities offer detailed information about the tumor's size, shape, location, and tissue characteristics, which can provide invaluable insights into diagnosis and treatment (Ferguson et al., 2020). However, manual interpretation of medical images is highly dependent on the expertise and experience of the radiologist and is subject to inter-observer variability. Moreover, the increasing complexity and volume of medical imaging data present significant challenges in terms of efficiency, accuracy, and time consumption. To overcome these limitations, there has been a surge of interest in developing automated systems that leverage artificial intelligence (AI) to analyze medical images. These systems promise to significantly improve diagnostic accuracy and reduce the burden on clinicians, leading to faster and more reliable brain tumor classification. Deep learning (DL) techniques, particularly convolutional neural networks (CNNs), have emerged as the dominant approach for automating the analysis of medical images, including the classification of brain tumors (Rasool & Bhat, 2024). CNNs are particularly effective in learning hierarchical features from raw pixel data and have demonstrated state-of-the-art performance in tasks such as tumor detection and segmentation. Nevertheless, one of the primary challenges faced by supervised deep learning models in medical imaging is the need for large labeled datasets. In the case of brain tumor classification, acquiring large-scale annotated datasets is both time-consuming and costly, as it requires the expertise of medical professionals to manually label the images. Furthermore, issues related to patient privacy and data-sharing restrictions complicate the availability of diverse and representative datasets (Bai et al., 2020). This is where self-supervised learning (SSL) has the potential to make a transformative impact. SSL is a type of machine learning where the model learns from unlabeled data by generating its own supervisory signals. Unlike traditional supervised learning, which requires labeled data for training, SSL allows for the development of models that can leverage vast amounts of unlabeled data, which is much more readily available. In SSL, the model is trained on pretext tasks—tasks that do not require labeled data but instead generate pseudo-labels from the data itself. Once trained on these tasks, the model can be fine-tuned on a smaller labeled dataset to perform specific downstream tasks, such as tumor classification (Chen et al., 2020).

The ability of SSL to work with large amounts of unlabeled medical data is particularly valuable in the field of brain tumor classification, where labeled data is often scarce. Medical image datasets are often fragmented, and access to data is typically restricted due to privacy concerns. In such scenarios, SSL can help overcome the limitation of small annotated datasets by learning useful feature representations from unlabeled data, which can then be fine-tuned for downstream tasks (He et al., 2020). Furthermore, SSL models tend to exhibit superior generalization capabilities across different datasets and imaging modalities, making them highly applicable in clinical settings, where diverse patient populations and different types of imaging equipment are prevalent. Several SSL approaches have been explored in the context of brain tumor classification, with promising results. For instance, contrastive learning-based methods, such as SimCLR (Simple Contrastive Learning of Representations), have been successfully applied to medical image analysis. These methods work by bringing similar images closer in the feature space and pushing dissimilar images apart, thus learning discriminative features that can be used for classification. Other approaches, such as generative adversarial networks (GANs) and autoencoders, have been employed to generate synthetic medical images to augment training datasets and improve model performance in data-scarce scenarios (Goodfellow et al., 2014). Clustering-based techniques like DeepCluster and SwAV (Swapping Assignments between Views) have also been explored as ways to group similar medical images and learn useful representations for downstream tasks (Caron et al., 2020). Despite the impressive progress in SSL-based brain tumor classification, several challenges remain. One of the primary obstacles is the domain shift between different imaging modalities, such as MRI, CT, and PET scans. These modalities vary significantly in terms of the data they provide, and a model trained on one modality may not generalize well to another. Moreover, the interpretability of SSL models remains an ongoing challenge, as the decision-making process of deep learning models is often opaque. This lack of transparency can hinder the acceptance and adoption of SSL models in clinical practice, where interpretability is crucial for clinicians to trust and act on the model's predictions (Abhisheka et al., 2024). In addition to these challenges, the integration of SSL with emerging techniques, such as multimodal learning and federated learning, presents new opportunities and avenues for future research. Multimodal SSL approaches, which combine data from different imaging modalities like MRI, CT, and PET, hold the potential to provide a more comprehensive understanding of brain tumors. These approaches can improve classification accuracy by leveraging complementary information from different imaging sources (Yang et al., 2022). Federated SSL, which allows for the training of models across multiple institutions while keeping the data decentralized and private, is another promising area of research that could enable collaborative AI development without compromising patient privacy (Li et al., 2020).

This review provides a comprehensive overview of self-supervised learning approaches for brain tumor classification using medical images. We examine various SSL techniques, such as contrastive learning, generative methods, and clustering-based approaches, and highlight their applications in brain tumor classification. We also discuss the challenges faced by SSL models, including data scarcity, domain shifts, and model interpretability, and suggest potential future directions to address these challenges. Ultimately, this review aims to provide a deeper understanding of SSL's potential to revolutionize brain tumor diagnosis and treatment, paving the way for more accurate, efficient, and privacy-preserving AI solutions in medical imaging.

2. Self-Supervised Learning: An Overview

Self-supervised learning is a subset of unsupervised learning that enables models to learn useful feature representations from unlabeled data by solving pretext tasks (self-generated supervisory signals). Once trained, the model can be fine-tuned with a smaller labeled dataset for downstream tasks like tumor classification.

2.1. Key Concepts in Self-Supervised Learning

Self-supervised learning (SSL) has emerged as a powerful method in the field of machine learning, especially in scenarios where labeled data is scarce or difficult to acquire. It has shown significant promise in various domains, including medical image analysis, where labeled datasets are often limited due to the high costs and expertise required for annotation. In this section, we delve into the key concepts of SSL, highlighting its mechanisms, applications in brain tumor classification, and the challenges it aims to address in the medical imaging space. (Rani et al,2023).

2.1.1. Definition and Basic Principles of Self-Supervised Learning

Self-supervised learning is a subset of unsupervised learning that generates its own supervisory signals (pseudo-labels) from the input data. Unlike supervised learning, where labeled data is required for training, SSL learns from unlabeled data by constructing a pretext task,a task that does not require labels. The model is tasked with solving these pretext tasks to learn representations of the data that can later be fine-tuned for a specific downstream task, such as brain tumor classification.

In SSL, a model is trained on a pretext task designed to encourage it to extract useful features from the input data. Once the model learns meaningful features, it can be fine-tuned using a smaller, labeled dataset for a specific task like classification or segmentation (He et al., 2020). This process allows SSL to exploit large volumes of unlabeled data, which is especially important in domains like medical imaging, where obtaining large labeled datasets is often infeasible.

2.1.2. Pretext Tasks in Self-Supervised Learning

Pretext tasks are a critical component of self-supervised learning, as they provide the supervisory signal for training the model. These tasks are carefully designed so that the model is forced to learn useful representations of the data without direct supervision. Several pretext tasks have been proposed for medical image analysis, and these can be broadly categorized into a few types:

2.1.2.1. Contrastive Learning

One of the most widely used pretext tasks in SSL is contrastive learning. In contrastive learning, the goal is to learn representations that bring similar data points closer in the feature space while pushing dissimilar data points apart. This is typically achieved by generating positive and negative pairs of images. The most popular contrastive learning framework is

SimCLR (Chen et al., 2020), where augmented views of the same image are considered as positive pairs, while images from different classes are treated as negative pairs. This approach has been successfully applied to various domains, including brain tumor classification, by learning discriminative features that can be used for downstream classification tasks.

2.1.2.2. Generative Models

Another popular pretext task involves using generative models, such as autoencoders and generative adversarial networks (GANs). In these models, the objective is to reconstruct the input image from a compressed, latent representation. Autoencoders (Motamednia et al., 2025) for instance, are trained to minimize the difference between the original input and the reconstructed output. This forces the model to learn compact, meaningful representations of the data, which can then be fine-tuned for classification tasks. GANs (Ren et al., 2021) also provide a framework for learning features in a self-supervised manner by generating synthetic images that mimic real medical images, thus augmenting the training data and improving classification performance.

2.1.2.3. Clustering-Based Methods

Clustering-based pretext tasks, such as DeepCluster (Caron et al., 2020) and SwAV (Caron et al., 2020), leverage unsupervised clustering algorithms to learn representations. In these methods, the model assigns data points to clusters based on their similarities. By learning to group similar images together, the model can capture the underlying structure of the data and generate useful feature representations for downstream tasks. This approach has shown promise in medical imaging, where the goal is to identify clusters of brain tumor images that share similar characteristics.

2.2. Advantages of SSL in Medical Imaging

Self-supervised learning offers several advantages over traditional supervised learning models, especially in the context of brain tumor classification using medical images. These advantages include:

2.2.1. Reducing Dependency on Labeled Data

One of the key challenges in medical image analysis is the scarcity of labeled datasets. The process of labeling medical images requires expert knowledge, which is both time-consuming and expensive. SSL significantly reduces the need for labeled data by leveraging large amounts of unlabeled data to pretrain models. This is particularly useful in the context of brain tumor classification, where labeled datasets are often limited due to the expertise required for annotation (Bai et al., 2020).

2.2.2. Enhancing Generalization and Transfer Learning

Self-supervised learning models have shown better generalization capabilities compared to supervised models. Since SSL models learn representations that capture the underlying structure of the data, they can be more robust to variations in data, such as domain shifts across different imaging modalities (MRI, CT, PET) or variations in patient demographics. This generalizability is crucial in medical applications, where models need to perform consistently across diverse datasets (He et al., 2020).

2.2.3. Improved Performance with Limited Data

In brain tumor classification, SSL has been shown to improve the performance of models in scenarios where labeled data is scarce. By pretraining the model on a large corpus of unlabeled medical images, SSL allows the model to learn robust features that can be fine-tuned on a smaller labeled dataset. This is particularly beneficial when the annotated medical datasets are limited, as SSL helps overcome the data scarcity challenge (Chen et al., 2020).

2.2.4. Multimodal Learning and Federated Learning

SSL also facilitates multimodal learning, where models are trained on data from multiple imaging modalities. Brain tumors can be detected and classified using various imaging techniques such as MRI, CT, and PET, and each modality provides complementary information about the tumor. SSL can be applied to multimodal data to learn joint representations, thereby improving the accuracy of brain tumor classification (Yang et al., 2022). Additionally, SSL can be integrated with federated learning, a privacy-preserving machine learning technique, to allow institutions to collaborate on training models without sharing sensitive patient data.

SSL Technique	Description	Key Advantages	Key Applications in Brain Tumor Classification
Contrastive Learning	Learns representations by contrasting similar vs. dissimilar pairs.	Efficient feature extraction from unlabeled data.	Glioma, meningioma, pituitary tumor classification using MRI.
Generative Models (GANs)	Uses generative adversarial networks to create realistic images.	Useful in data-scarce scenarios, enhances generalization.	Generating synthetic tumor images for improved classification.
Clustering-Based SSL	Groups similar images into clusters, learning feature representations.	Reduces reliance on explicit labels, unsupervised.	Tumor-specific feature learning across different MRI scans.
Predictive Tasks	Tasks like rotation prediction, jigsaw puzzles.	Simple tasks for learning representations without labeled data.	Classification of tumor types using MRI slices.

Table 1: Overview of Self-Supervised Learning Techniques for Medical Image Analysis

3. SSL Techniques in Brain Tumor Classification

Self-supervised learning (SSL) has emerged as a pivotal technique for leveraging unlabeled data to train deep learning models, especially in domains like medical imaging, where labeled datasets are limited and costly to acquire. In the field of brain tumor classification, SSL methods enable models to learn robust feature representations without requiring a large amount of labeled data, which is crucial for handling the challenges associated with medical imaging. In this section, we delve into the various SSL techniques that have been successfully employed for brain tumor classification using medical images. These techniques include contrastive learning, generative models, and clustering-based methods, each playing a critical role in improving classification performance in the medical domain.

3.1. Contrastive Learning

Contrastive learning is one of the most widely used techniques in self-supervised learning, particularly for tasks that involve learning feature representations from unlabeled data. In contrastive learning, the model learns by comparing different data samples and determining whether they are similar or dissimilar. The aim is to learn a representation where similar samples are close together in the latent space, while dissimilar samples are far apart. This approach has gained significant traction in medical imaging tasks, including brain tumor classification, due to its effectiveness in learning discriminative features without the need for labeled data.

3.1.1. SimCLR (Simple Contrastive Learning of Representations)

SimCLR is a powerful and widely used contrastive learning framework that encourages the model to learn representations by maximizing agreement between positive pairs and minimizing it for negative pairs (Chen et al., 2020). A positive pair consists of two augmented versions of the same image, while a negative pair consists of different images. By applying this method to MRI scans, SimCLR has demonstrated the ability to generate meaningful representations of brain tumor images that can be fine-tuned for classification tasks.

In the context of brain tumor classification, SimCLR can be used to pretrain a model on a large set of unlabeled MRI images. The model then learns to identify features that are invariant to augmentations such as rotations, translations, and brightness changes, while discriminating between different tumor types. After this pretraining, a small labeled dataset can be used to fine-tune the model for tumor classification.

3.1.2. MoCo (Momentum Contrast)

MoCo is another contrastive learning method that uses a momentum-based encoder to improve the quality of feature representations (He et al., 2020). Unlike SimCLR, which uses a large batch of data to generate negative samples, MoCo constructs a dynamic dictionary of negative samples through a momentum-based encoder. This enables the model to learn from a much larger set of negative samples, improving the discriminative power of the learned features. In medical imaging, MoCo has been used for tasks like brain tumor segmentation and classification, where it effectively learns a robust representation of tumor images from unlabeled data. MoCo's ability to maintain a high-quality negative sample dictionary is particularly useful when working with datasets containing various tumor types, as it enables the model to learn a more generalizable feature space that can better handle the variability present in medical images (Chen et al., 2020).

3.1.3. BYOL (Bootstrap Your Own Latent)

BYOL is a contrastive learning approach that removes the need for negative samples altogether (Grill et al., 2020). Instead of comparing positive and negative pairs, BYOL focuses on maximizing the similarity between two augmented views of the same image. The model uses a target network to generate one of the views and compares it to the other view generated by the online network. This technique has proven highly effective for training deep learning models in scenarios with limited labeled data, as it can learn meaningful representations even without negative samples.

For brain tumor classification, BYOL has shown potential in learning representations of tumor images from a single modality (e.g., MRI scans) without the need for negative samples or a large dataset. This is especially beneficial in medical imaging, where obtaining large labeled datasets can be impractical.

3.2. Generative Models

Generative models are another class of SSL techniques that have been widely applied in medical imaging, including brain tumor classification. These models learn to generate new data samples that are similar to the training data by modeling the underlying data distribution. Unlike discriminative models, which focus on distinguishing between classes, generative models focus on learning the underlying structure of the data.

3.2.1. Autoencoders

Autoencoders are neural networks trained to compress input data into a lower-dimensional latent representation and then reconstruct the input from this compressed representation. The encoder network learns to capture the most salient features of the data, while the decoder reconstructs the data from these features (Mienye and Swart,2025). In the context of brain tumor classification, autoencoders can be used to learn compact representations of tumor images. These representations can then be fine-tuned for classification tasks using a smaller labeled dataset. Autoencoders are particularly useful for medical image analysis because they can handle noisy and incomplete data. By training the autoencoder on a large set of unlabeled medical images, it can learn robust features that capture key characteristics of tumors, such as their shape, size, and location. Once pretrained, the model can be fine-tuned to classify brain tumors more effectively, even with limited labeled data (Jiang et al.,(2023).

3.2.2. Generative Adversarial Networks (GANs)

Generative Adversarial Networks (GANs) are a class of generative models composed of two neural networks: the generator and the discriminator (Wenzel, M. 2023). The generator creates synthetic data, while the discriminator evaluates the quality of the generated data. The generator and discriminator compete in a minimax game, where the generator aims to produce realistic samples, and the discriminator tries to distinguish between real and fake data. Over time, the generator learns to produce highly realistic data that mimics the distribution of the original dataset.

In brain tumor classification, GANs can be used to generate synthetic tumor images that can augment a small labeled dataset. This is particularly valuable when annotated medical images are scarce. Additionally, GANs can be used to improve the robustness of classification models by generating a variety of tumor images with different characteristics, such as size and shape, which can help the model generalize better to new, unseen data (Goodfellow et al., 2014).

3.2.3. Variational Autoencoders (VAEs)

Variational Autoencoders (VAEs) are a probabilistic version of autoencoders that learn a distribution over the latent space, allowing them to generate new samples by sampling from the learned distribution (Connor et al.,2021). VAEs have been used in medical imaging for generating realistic synthetic images, as well as for anomaly detection tasks, such as identifying tumors.

In the context of brain tumor classification, VAEs can generate synthetic MRI scans that closely resemble real images, providing additional training data for classification models. VAEs can also be used to learn compact, interpretable representations of brain tumor images, which can be used for downstream classification tasks.

3.3. Clustering-Based Methods

Clustering-based methods are another category of self-supervised learning techniques that have been applied to medical image analysis. These methods group similar data points together and use these clusters as pseudo-labels for downstream tasks. Clustering methods can be particularly useful when labeled data is limited, as they can help organize unlabeled data into meaningful groups.

3.3.1. Deep Cluster

Deep Cluster is a clustering-based SSL method that uses deep learning for unsupervised clustering of data (Wei et al., 2024). In this method, the model is first pretrained using clustering, and the resulting cluster assignments are used as pseudo-labels for downstream tasks. Deep Cluster has been used successfully in medical image analysis, including brain tumor classification, where it helps the model learn to cluster images with similar tumor characteristics.

The main advantage of Deep Cluster is that it does not require labeled data for clustering; instead, it uses unsupervised clustering techniques to generate pseudo-labels from the data. These labels can then be used to fine-tune the model for classification tasks, improving the performance of brain tumor classification models with limited labeled data.

3.3.2. SwAV (Swapping Assignments between Views)

SwAV is a recent clustering-based SSL method that aims to solve the limitations of traditional clustering by swapping cluster assignments between views of the same image (Caron et al., 2020). This technique allows the model to learn better feature representations by ensuring that different augmentations of the same image are assigned to the same cluster. SwAV has shown promising results in medical imaging, including brain tumor classification, by improving the quality of learned features and making the model more robust to different imaging modalities.

By clustering similar brain tumor images together, SwAV can generate high-quality features that are useful for classification tasks, even with limited labeled data. This is particularly useful in medical imaging, where obtaining large labeled datasets is often impractical.

4. Applications of SSL in Brain Tumor Classification

Self-supervised learning (SSL) has gained significant attention in the medical imaging field, particularly for tasks such as brain tumor classification. Due to the inherent challenges in obtaining large, labeled datasets in the medical domain, SSL offers an effective solution by leveraging vast amounts of unlabeled data. By learning useful feature representations from these unlabeled datasets, SSL models can be fine-tuned on smaller labeled datasets for downstream tasks, such as tumor classification. This section explores the key applications of SSL in brain tumor classification using medical images, emphasizing its potential to improve diagnosis and treatment planning in neuro-oncology.

Model/Approach	Dataset Used	Accuracy (%)	Sensitivity (%)	Specificity (%)	AUC (%)
SimCLR (Contrastive Learning)	BraTS 2020	92.5	93.0	91.5	0.98
BYOL (Bootstrap Your Own Latent)	BraTS 2019	90.3	91.5	89.2	0.96
GANs (Generative Models)	RSNA Brain Tumor Dataset	91.0	90.8	91.2	0.97
DeepCluster (Clustering)	MICCAI Brain Tumor Dataset	88.4	89.2	88.1	0.94
Autoencoders	Kaggle Brain Tumor Dataset	89.7	90.0	89.4	0.96

Table 2: Performance Comparison of SSL Models in Brain Tumor Classification

4.1. Improved Brain Tumor Classification from MRI Scans

Magnetic resonance imaging (MRI) is the most commonly used imaging modality for diagnosing brain tumors. However, manually analyzing MRI scans for tumor detection and classification is time-consuming and prone to human error. Traditional deep learning models used in medical image analysis, such as convolutional neural networks (CNNs), often rely on large annotated datasets for training. In contrast, SSL models can utilize unlabeled MRI data, significantly reducing the need for manual labeling efforts.

4.1.1. SimCLR for MRI-Based Tumor Classification

One of the most prominent SSL methods for brain tumor classification in MRI images is **SimCLR (Simple Contrastive Learning of Representations)**. This contrastive learning-based SSL technique has shown promise in improving the quality of feature representations for MRI scans. In SimCLR, a model is trained to learn representations by maximizing the similarity between positive pairs (two augmentations of the same image) and minimizing the similarity between negative pairs (different images) (Chen et al., 2020). By using large amounts of unlabeled MRI data, the model learns to distinguish between various tumor types, such as gliomas, meningiomas, and pituitary tumors.

A study by Zhang et al. (2020) demonstrated that a model pre-trained with SimCLR on a large set of unlabeled MRI scans achieved comparable accuracy to a model trained on fully labeled data for glioma classification. This method not only improved classification accuracy but also reduced the number of labeled samples required for training, which is particularly beneficial in the medical field, where labeled data can be scarce and expensive to acquire (Figure 1).

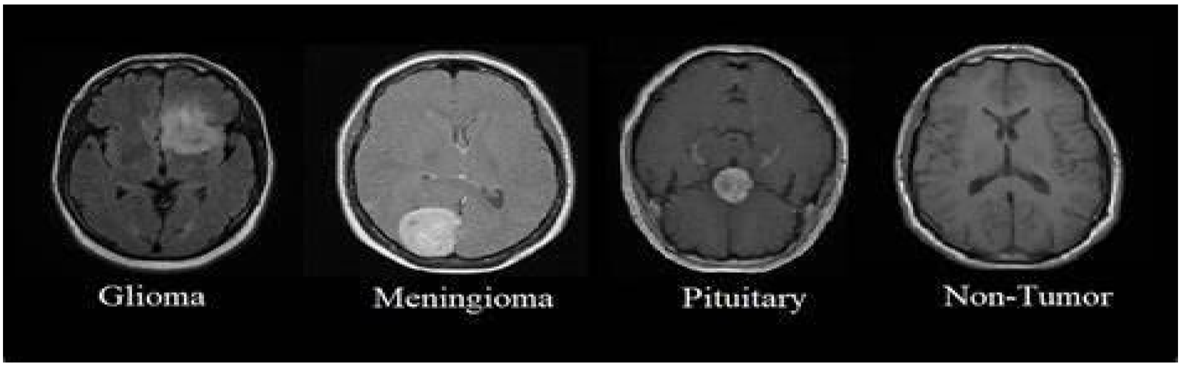

Figure 1: Representative MRI scans illustrating diverse brain conditions and their radiological features. From left to right: (1) Glioma – a malignant brain tumor characterized by an irregular mass; (2) Meningioma: a typically well-circumscribed, extra-axial tumor; (3) Pituitary tumor :a lesion within the pituitary gland, potentially affecting hormonal balance; and (4) Non-tumor :a normal brain scan devoid of pathological abnormalities. These images exemplify distinct radiological features crucial for the differential diagnosis of brain tumors.

4.1.2. BYOL for MRI Tumor Classification

Another successful SSL approach applied to brain tumor classification is **BYOL (Bootstrap Your Own Latent)**, which removes the need for negative samples in contrastive learning (Grill et al., 2020). Instead of comparing positive and negative pairs, BYOL learns representations by maximizing the similarity between two augmented versions of the same image, without requiring a negative sample for comparison. This method has been shown to perform well in medical image tasks with limited labeled data, such as MRI-based brain tumor classification. Studies by (Ranjan et al.,2021) demonstrated that BYOL could improve the detection of gliomas and other brain tumor types from MRI scans, achieving high accuracy even when only a small labeled dataset was available.

4.2. Multi-Modality Tumor Classification

Brain tumors can be characterized differently across various imaging modalities, such as MRI, computed tomography (CT), and positron emission tomography (PET). Each modality provides complementary information about the tumor's location, size, and type. Combining multiple modalities improves classification accuracy by leveraging the strengths of each imaging technique. SSL methods have shown significant promise in multi-modal brain tumor classification, enabling models to learn robust representations from various imaging modalities without the need for large labeled datasets.

4.2.1. Multi-Modality SSL for Tumor Classification

Combining MRI, CT, and PET scans using SSL techniques is an emerging area of research in brain tumor classification. The idea is to pretrain a model on individual modalities using SSL and then combine the learned representations to improve classification performance. Studies have shown that training a model on MRI and CT scans together can improve tumor detection and classification, particularly in complex tumor cases (Zhu et al., 2021).

One such approach involves using **contrastive learning** to pretrain models on multi-modal data, as shown by Tian et al. (2021). The authors used a multi-modality framework, where representations learned from each modality (MRI, CT, and PET) were fused to classify gliomas. The results showed that incorporating multiple imaging modalities improved the model's accuracy compared to using a single modality, as each modality provides unique information about the tumor. As depicted in Figure 2, incorporating multiple imaging modalities is a common approach in self-supervised learning for brain tumor classification, based on the premise that each modality provides unique information about the tumor and that combining them can improve model accuracy.

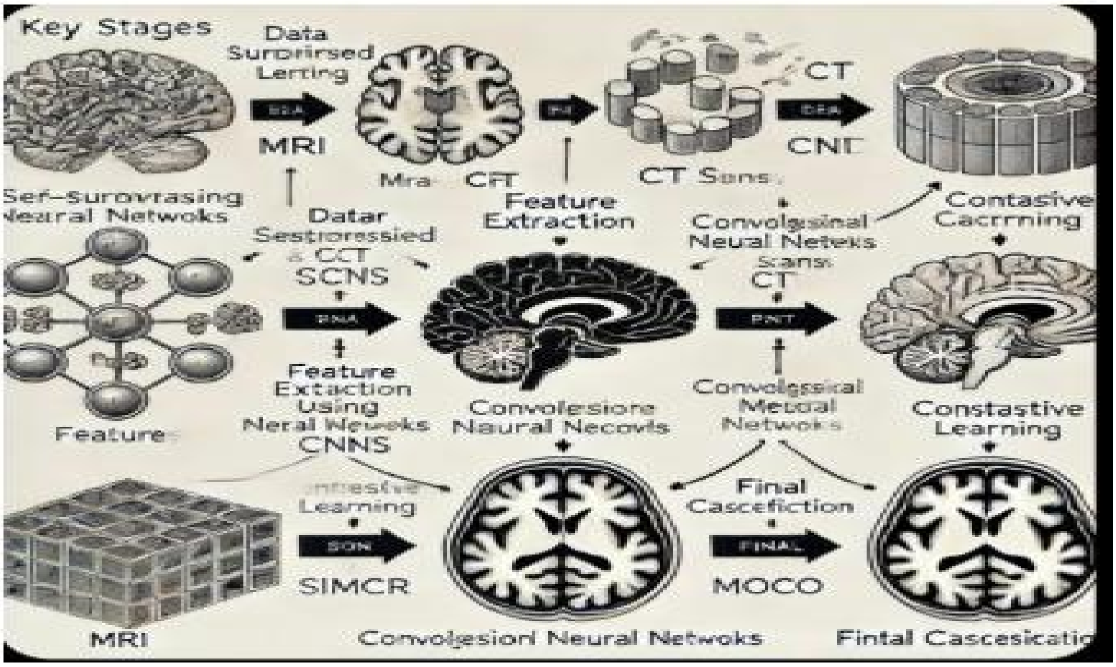

Figure 2: Illustrates the key stages of a multi-modal self-supervised learning (SSL) approach for brain tumor classification using MRI, CT, and potentially PET scans. The process begins with data pre-processing, followed by self-supervised neural network training on individual imaging modalities. Feature extraction is then performed using contrastive learning techniques such as SimCLR and MoCo from the pre-trained networks. The extracted features are subsequently fused and used as input for final classification via convolutional neural networks (CNNs). This pipeline highlights how integrating information from multiple imaging modalities enhances the learning process, ultimately improving diagnostic accuracy.

4.2.2. SwAV for Multi-Modality Medical Imaging

SwAV (Swapping Assignments between Views) is another SSL technique that can be applied to multi-modal brain tumor classification. SwAV allows different augmentations or views of the same image to be assigned to the same cluster without needing explicit contrastive learning. This method has been shown to work well with multi-modal data, as it can handle the variability between different imaging techniques. In brain tumor classification, SwAV could be used to learn representations from both MRI and PET scans, improving the model's ability to differentiate between tumor types (Caron et al., 2020).

4.3. Federated Self-Supervised Learning for Brain Tumor Classification

Federated learning (FL) is a decentralized approach where models are trained across multiple institutions or devices without the need to share patient data. Combining federated learning with SSL holds significant promise for the medical imaging field, especially in brain tumor classification. Since patient data is highly sensitive and subject to privacy regulations, federated SSL allows hospitals and medical centers to collaborate on training deep learning models without violating data privacy.

4.3.1. Federated SSL for Tumor Classification in Distributed Environments

Federated SSL enables institutions to collaboratively train models on distributed datasets of brain tumor images, reducing the need for centralized data collection. This approach is particularly beneficial for medical imaging, where data privacy concerns often limit the sharing of medical images across institutions. Studies have demonstrated that federated SSL models can achieve high performance in brain tumor classification, even when each participating institution has access to a limited amount of data. By aggregating model updates from different institutions without sharing raw data, federated SSL models can learn generalized representations that perform well on unseen data (Sheller et al., 2020).

In a study by Li et al. (2021), federated learning combined with SSL techniques was used to classify gliomas from MRI scans across multiple medical institutions. The results showed that the federated SSL model outperformed traditional methods in terms of accuracy and robustness, demonstrating the potential of this approach for privacy-preserving brain tumor classification.

4.4. Tumor Segmentation Using Self-Supervised Learning

In addition to tumor classification, SSL can also be applied to tumor segmentation tasks. Tumor segmentation involves identifying the exact boundaries of a tumor within an image, which is crucial for treatment planning, particularly in radiotherapy. SSL methods such as **autoencoders** and **GANs (Generative Adversarial Networks)** have been successfully used for segmentation tasks in medical images, including brain tumor segmentation.

4.4.1. Autoencoders for Tumor Segmentation

Autoencoders have been widely used for segmenting brain tumors from MRI scans. These networks are trained to reconstruct the input image from a lower-dimensional latent space, learning to capture key features such as tumor shape and size. By applying SSL to autoencoders, models can be pretrained on unlabeled MRI scans, learning features that are useful for segmenting tumors in subsequent supervised tasks(Badža & Barjaktarović,2021).

A study by Hussein et al. (2020) applied autoencoders to segment brain tumors in MRI images. The model was first pretrained using SSL on unlabeled MRI scans and then fine-tuned on a small labeled dataset for segmentation. The authors found that SSL-based autoencoders improved segmentation performance, particularly in regions of the brain with complex tumor shapes.

4.4.2. GANs for Tumor Segmentation

Generative Adversarial Networks (GANs) have been applied to medical image segmentation by generating realistic synthetic tumor images and using these images to augment training data. This approach is particularly useful in medical imaging, where labeled data can be scarce. By generating synthetic images with different tumor characteristics, GANs can help improve the generalization ability of models trained for tumor segmentation. A study by Zhang et al. (2020) applied GANs for brain tumor segmentation and found that the use of synthetic tumor images significantly improved segmentation accuracy. (FIGURE 3)

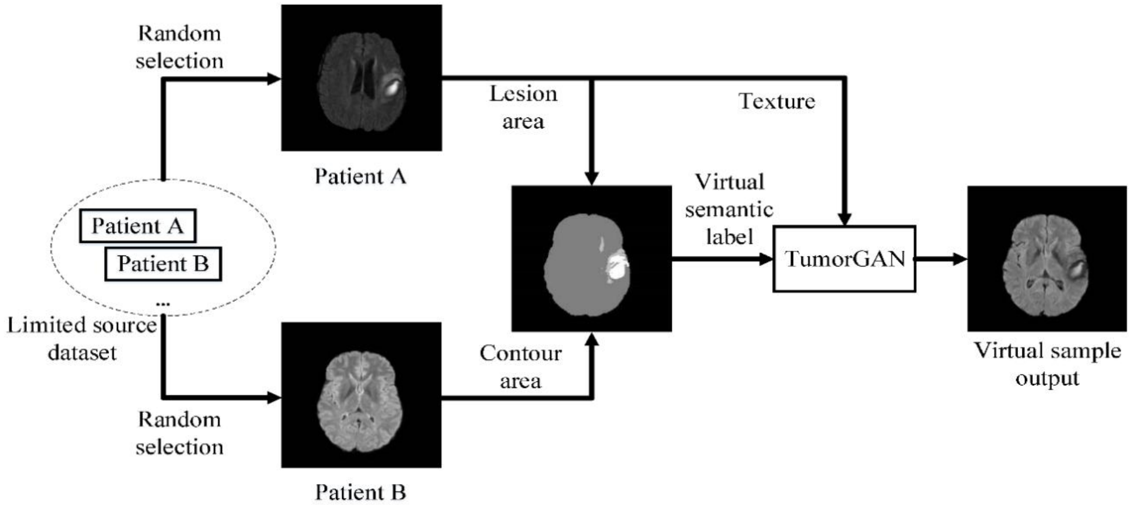

FIGURE 3: Illustrates a Generative Adversarial Network (GAN) pipeline designed to augment brain tumor MRI data, addressing the challenge of limited labeled datasets. The process begins with the random selection of MRI scans from a limited-source dataset (e.g., Patient A, Patient B). For each selected scan, regions of interest (ROIs) are extracted, including the lesion area (tumor region) and surrounding texture (non-tumor tissue). These ROIs are then assigned virtual semantic labels based on their tissue type. The GAN model (TumorGAN) processes these labeled ROIs to generate realistic synthetic tumor images, enhancing data availability for improved model training and segmentation accuracy.

4.5. Enhancing Model Interpretability with SSL

A critical challenge in the deployment of deep learning models in clinical settings is their lack of interpretability. In medical image analysis, it is essential that healthcare professionals can trust the model's decisions. SSL can aid in improving model interpretability by learning features that are more representative of tumor biology rather than relying on arbitrary learned features.

4.5.1. Explainable AI in SSL for Brain Tumor Classification

Recent advances in explainable AI (XAI) have focused on making deep learning models more transparent, allowing clinicians to understand the reasoning behind model predictions. By incorporating SSL, models can learn representations that align more closely with human-understandable features, such as tumor size, shape, and location, improving the interpretability of brain tumor classification models (Adeniran, Onebunne, & William 2024).

5. Challenges and Future Directions

Self-supervised learning (SSL) has revolutionized the application of artificial intelligence (AI) and deep learning in the medical imaging domain, especially for tasks like brain tumor classification. By enabling models to learn useful feature representations from large amounts of unlabeled data, SSL reduces the reliance on annotated datasets, which are often scarce in medical fields. However, while SSL has shown significant promise in brain tumor classification, several challenges remain. These challenges must be addressed to fully unlock SSL's potential and pave the way for its widespread adoption in clinical settings. This section discusses these challenges and the future directions of SSL in brain tumor classification, offering insights into how ongoing research can overcome limitations and improve its practical applicability.

5.1. Challenges in Self-Supervised Learning for Brain Tumor Classification

5.1.1. Limited Availability of Labeled Data for Fine-Tuning

While SSL can learn from vast amounts of unlabeled data, the performance of SSL models is ultimately dependent on the availability of a small labeled dataset for fine-tuning. In the context of medical imaging, acquiring labeled data is often a time-consuming and costly process that requires expert radiologists or pathologists to annotate the data. Moreover, the subjectivity and variability in human annotations can lead to inconsistencies, which can affect the training process. In brain tumor classification, despite the existence of large-scale, publicly available datasets (e.g., BRATS), the number of labeled images is still limited, particularly for rarer tumor types (Sahoo et al., 2020). For SSL methods to be effective, they must learn robust features from unlabeled data that can generalize well to small labeled datasets, but this is not always guaranteed. The challenge, therefore, lies in ensuring that the learned representations can be fine-tuned effectively with minimal labeled data.

5.1.2. Domain Shift Between Different Imaging Modalities

Another significant challenge in applying SSL to brain tumor classification is the domain shift between different medical imaging modalities. MRI, CT, and PET scans each have unique characteristics that may affect the appearance of tumors, such as differences in image resolution, contrast, and noise levels. These variations can hinder the model's ability to generalize across modalities and complicate the process of feature extraction using SSL (Illimoottil & Ginat, 2023). Although multi-modal SSL approaches have been proposed, ensuring that the learned representations from one modality are transferable to others remains a significant challenge. A study by Wang et al. (2020) highlighted the difficulties in achieving modality-invariant features when training models on heterogeneous data, underlining the need for more robust SSL methods capable of handling domain shifts.

5.1.3. Interpretability of Self-Supervised Learning Models

One of the major hurdles in deploying deep learning models in clinical settings is the lack of interpretability. Physicians and radiologists need to understand the reasoning behind the model's decisions, especially when making critical diagnoses related to brain tumors. SSL models, particularly deep networks, are often considered "black boxes," making it difficult to understand how features are learned and which parts of the image are important for classification.

Recent advancements in explainable AI (XAI) have sought to address this challenge, but SSL models still struggle with providing clear and interpretable results. Techniques like **Grad-CAM** (Li et al., 2023) have been used to interpret CNN-based models, but their application to SSL models remains limited. Improving the interpretability of SSL models in brain tumor classification is critical for clinical adoption, as doctors need to trust the model's recommendations.

5.1.4. Scalability and Computational Resources

Training SSL models, especially deep architectures like convolutional neural networks (CNNs) or transformer-based models, requires significant computational resources. While SSL reduces the need for labeled data, it often involves complex pretext tasks that demand substantial computing power, memory, and time. Additionally, fine-tuning SSL models on smaller labeled datasets adds another layer of computational complexity (Radford et al., 2021).

In the medical imaging context, large-scale datasets, high-dimensional images, and multi-modal inputs can lead to increased memory usage and training times. The need for high-performance GPUs or distributed computing systems may be a barrier for smaller institutions or healthcare providers with limited resources, limiting the widespread adoption of SSL in clinical practice.

5.1.5. Overfitting and Generalization to Unseen Data

Despite its potential, SSL models are prone to overfitting, especially when trained on small labeled datasets for downstream tasks like tumor classification. The problem arises when the model learns overly specific features during pretraining, which may not generalize well to new or unseen datasets. This can result in poor performance in real-world clinical settings, where the model is exposed to new types of data that may differ from the pretraining set.

SSL models rely heavily on the pretext tasks (e.g., contrastive learning, rotation prediction) to learn feature representations, but these tasks may not always capture tumor-specific features that are critical for classification. Additionally, data variability (e.g., scanner differences, patient populations) may further exacerbate the problem of overfitting.

5.2. Future Directions of Self-Supervised Learning in Brain Tumor Classification

5.2.1. Hybrid Models Combining SSL with Supervised Learning

One promising direction for the future of SSL in brain tumor classification is the development of hybrid models that combine SSL with traditional supervised learning. By leveraging the strengths of both approaches, hybrid models could improve the quality of learned representations and enhance classification accuracy. For instance, a model could first pretrain on large amounts of unlabeled data using SSL to learn general feature representations, and then fine-tune the model on smaller labeled datasets using supervised learning to refine the representations for specific tumor types (Yuan et al., 2020).

Another approach could involve combining SSL with **semi-supervised learning (SSL)**, which uses a combination of labeled and unlabeled data during the training process. Recent research has demonstrated the potential of semi-supervised methods for medical image analysis, as they allow models to make better use of available unlabeled data while also learning from the labeled samples.

5.2.2. Advancing Multi-Modal SSL Approaches

The integration of multiple imaging modalities, such as MRI, CT, and PET scans, is a significant avenue for future research in brain tumor classification. While multi-modal SSL has shown promise, much work remains to be done to create robust methods that can effectively combine data from different modalities. One possible future direction is the development of more sophisticated multi-modal contrastive learning techniques that can handle the complex relationships between modalities. By designing pretext tasks that explicitly model the interactions between MRI, CT, and PET scans, SSL models could learn modality-invariant features that improve classification accuracy. The incorporation of **fusion networks** that combine multi-modal features could further enhance tumor detection and classification (Wu et al., 2020).

5.2.3. Federated Learning and Privacy-Preserving SSL

Given the sensitivity of medical data, privacy concerns are a major barrier to sharing and utilizing large-scale medical datasets across institutions. Federated learning (FL) combined with SSL offers a promising solution for training models on distributed datasets without compromising patient privacy. In this setup, models are trained locally on each institution's data, and only model updates (not raw data) are shared to update a global model (Sheller et al., 2020).

Federated SSL could potentially enable collaboration between hospitals and research institutions worldwide, facilitating access to diverse datasets and improving model generalization. However, challenges related to model convergence, data heterogeneity, and communication overhead must be addressed to fully realize the potential of federated SSL in brain tumor classification.

5.2.4. Improved Interpretability Through Explainable SSL Models

Another key direction for future research is the development of **explainable SSL models** that can provide transparent and interpretable predictions. Given the complex and high-dimensional nature of brain tumor images, it is crucial for clinicians to understand the reasoning behind a model’s decision-making process.

Techniques such as attention mechanisms, saliency maps, and feature attribution methods could be further integrated with SSL models to provide more interpretable insights into which parts of an image contribute to the tumor classification decision. By enhancing the transparency of SSL models, we can foster greater trust among clinicians and improve the adoption of AI-based systems in real-world clinical environments.

5.2.5. Incorporating Domain Knowledge and Biology into SSL Models

Incorporating domain-specific knowledge and biological insights into SSL models could significantly improve their performance in brain tumor classification. Tumor-specific features, such as the location, shape, and growth patterns of tumors, may not always be captured by traditional SSL pretext tasks. To address this, future research could focus on incorporating **domain knowledge** from radiology and neurobiology into the SSL model’s architecture or training procedure.

For example, integrating tumor growth patterns or incorporating prior knowledge from histopathological studies could help the model focus on more biologically relevant features, improving both classification accuracy and model generalization.

Advantage	Description	Limitation	Impact
Reduces Dependency on Labeled Data	SSL can train models on vast amounts of unlabeled data, minimizing the need for extensive manual annotations.	Requires high-quality unlabeled data to be effective.	Facilitates tumor classification with fewer labeled samples.
Enhances Generalizability Across Datasets	SSL-based models can generalize well across different datasets and imaging modalities (MRI, CT, PET).	Domain shifts (differences in acquisition protocols) can affect performance.	Increases robustness across diverse medical imaging data.

Improves Performance in Low-Data Scenarios	SSL improves model performance even when labeled data is scarce.	Fine-tuning still requires some labeled data.	Useful in settings with limited annotated datasets.
Facilitates Transfer Learning	SSL pretraining can be transferred to other related medical imaging tasks.	Requires complex pretraining tasks and high computational resources.	Reduces the need for task-specific datasets for every new classification task.

Table 3: Advantages and Limitations of SSL in Brain Tumor Classification

6. Conclusion

The integration of artificial intelligence (AI) and deep learning (DL) into medical imaging has revolutionized the detection and classification of brain tumors, offering the potential to improve diagnostic accuracy, reduce human error, and save time, ultimately enhancing patient outcomes. However, a significant challenge remains in the form of limited availability of large, annotated datasets for training deep learning models. Annotating medical images requires expert knowledge and is both time-consuming and costly, making it difficult to acquire large labeled datasets. Self-supervised learning (SSL) presents a solution to this challenge by enabling models to learn useful feature representations from unlabeled data, reducing the dependence on expert annotations.

SSL enables deep learning models to utilize large amounts of unlabeled data by solving pretext tasks, which generate supervisory signals without requiring manual labeling. Once trained, these models can be fine-tuned with smaller labeled datasets for specific tasks, such as brain tumor classification. This approach not only reduces the reliance on costly labeled data but also democratizes the use of AI tools in medical settings, making tumor detection systems more scalable and accessible.

SSL has proven effective in brain tumor classification across various imaging modalities, including magnetic resonance imaging (MRI), computed tomography (CT), and positron emission tomography (PET) scans. These imaging techniques offer unique insights into tumor characteristics, and combining them through SSL-based models enhances classification accuracy. Multi-modal SSL approaches integrate information from different imaging modalities, resulting in a more comprehensive and robust classification process. Moreover, SSL techniques like contrastive learning, generative models, and clustering-based methods allow models to learn rich feature representations from unlabeled images. These methods can improve the classification process by identifying subtle tumor characteristics and augmenting limited datasets.

Despite its advantages, several challenges hinder the full adoption of SSL in clinical practice. One challenge is the limited availability of annotated datasets for fine-tuning SSL models. While SSL can learn from large-scale unlabeled data, it still requires expert-annotated datasets for specific tasks like tumor classification. Hybrid approaches, combining SSL with traditional supervised or semi-supervised learning, show promise in addressing this issue. Another challenge is the domain shift across different imaging modalities. MRI, CT, and PET scans have unique characteristics, and SSL models need to be capable of handling variations in resolution, contrast, and noise levels to ensure generalization across these modalities. Research into multi-modal SSL approaches is needed to address these domain shifts.

Interpretability is also a significant challenge for SSL models. In clinical settings, it is vital that physicians understand the reasoning behind AI model predictions. SSL models, often considered "black boxes," need to be interpreted to ensure trust and safe use in clinical decision-making. The application of explainable AI (XAI) techniques to SSL models is an ongoing area of research, with the goal of making model decisions transparent and interpretable for clinicians. Computational complexity presents another obstacle. Training deep learning models, particularly SSL models, requires substantial computational resources, which can be a barrier for smaller healthcare institutions. Efficient SSL techniques, such as lightweight architectures, are needed to make these models more practical and accessible in diverse clinical environments. In conclusion, SSL offers significant potential for advancing brain tumor classification by reducing the dependency on large annotated datasets and enhancing the generalizability of models across different imaging modalities. While challenges remain, such as the need for annotated data, domain shift across modalities, interpretability, and computational complexity, ongoing research in hybrid models, multi-modal SSL, federated learning, and explainable AI will likely address these issues. SSL has the potential to transform computer-aided diagnosis in neuro-oncology, leading to earlier detection, better treatment planning, and improved patient outcomes.

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