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Advancements in brain tumor classification: a survey of transfer learning techniques

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ABSTRACT

This survey article presents a critical review of the state-of-the-art transfer learning (TL) methodologies applied in the field of brain tumor classification, with a special emphasis on their various contributions and associated performance metrics. We will discuss various pre-processing approaches, the underlying fine-tuning strategies, whether used purely or in an end-to-end training manner, and multi-modal applications. The current study specifically highlights the application of VGG16 and residual network (ResNet) methods for feature extraction, demonstrating that leveraging high-order features in magnetic resonance imaging (MRI) images can enhance accuracy while reducing training. We further analyze fine-tuning methods in relation to their role in optimizing model layers for small, domain-specific datasets, finding them particularly effective in enhancing performance on the small brain tumor dataset. It will look into end-to-end training, which means fine-tuning models that have already been trained on large datasets to make them better. It will also present multimodal TL as a way to use both MRI and computed tomography (CT) scan data to get better classification results. Comparing different pre-trained models can provide a better understanding of the strengths and weaknesses associated with the particular brain tumor classification task. This review aims to analyze the advancements in TL for medical image analysis and explore potential avenues for future research and development in this crucial field of medical diagnostics.

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1. INTRODUCTION

One of the essential diagnostic tasks in medicine is the classification of brain tumors, which aims to recognize various types of brain tumors and distinguish them from each other to establish an appropriate treatment plan. The type and stage of brain tumor determine the treatment and the prognosis; therefore, proper diagnosis is crucial in enhancing patient outcomes [1], [2]. Magnetic resonance imaging (MRI) and computed tomography (CT) scans are the most preferred modalities used in the diagnosis of conditions affecting the brain because of the high resolution and non-invasive technique used in their execution [3]. MRI is especially helpful because of the high contrast of soft tissues [4] and is therefore very valuable in the detection of brain tumors, their size, location, and malignancy. Its ability to provide high-definition images of anatomical structures, especially the brain, makes it the gold standard for brain tumor diagnosis. CT, or computerized tomographic imaging, provides cross-section pictures of the brain using X-rays and is faster and more accessible than MRI. It can also be helpful in cases of head trauma. They are also useful in viewing calcifications, which can sometimes be difficult to visualize in an MRI scan, and in identifying bone involvement. Despite the difference in the given advantages of both modalities, in clinical practice, they work together and give an overall view of the tumor and its boundaries. Recent improvements in ML, DL, and TL have proven to be useful in improving the process of automatic detection and characterization of brain tumors from these imaging techniques. By combining MRI and/or CT images, emerging computational techniques enable more accurate tumor classification [5], [6] thereby reducing the radiologists' workload. These combined imaging modalities with new computational concepts have extended applications and the possibility of increased diagnosis accuracy and faster, less invasive diagnosis of brain tumors, which has positive impacts on patients' care and treatment.

The relevant detailed literature survey is described here. The first five investigations in the BC brain tumor classification literature present various novel strategies for enhancing the precision and speed of BC diagnostic results. Study [1] specifically designed a novel convolutional neural network (CNN) architecture to classify three types of brain tumors from MRI images: meningiomas, gliomas, and pituitary tumors. The study utilized contrast-enhanced T1 MRI images and demonstrated that their proposed CNN model classifies the images with an accuracy of 92%, outperforming the previous methods. They achieved a 50% improvement in accuracy using relent-less ten-fold cross-validation on enhanced picture repositories. This model-based strategy's features also showcase its potential as an instrument for medical diagnosis. In line with study [7], which identified the need for automatic classification of brain tumor types. They presented an automated approach that involved enhancing images for better visualization, followed by feature extraction using two pre-trained deep learning (DL) models presented an automated approach that involved enhancing images for better visualization, followed by feature extraction using two pre-trained deep learning (DL) models. The PLS compiles all these features into a single hybrid vector, and agglomerative clustering identifies the tumor location. Ultimately, employ EfficientNet-B0 for the final classification. This method successfully classified the datasets with a high accuracy of approximately 95%. The accuracy in diagnosing meningioma, glioma, and pituitary tumors was particularly high, with 98% accuracy, respectively. 31%, 98.72%, and 99.46%, respectively. This is an effective solution to the problems associated with manual classification since this method offers an almost 100% automated process. The study [8] designed an approach that incorporated DL and important image processing methods based on the EfficientNet model to improve the performance of brain tumor classification. Preprocessing of MRI images was performed using cropping, resizing, denoising, and normalization techniques; feature extraction was done using DenseNet121, and the model uses sigmoid activation for the classification. The obtained results showed fairly high recalls, ranging from 87% to a peak of 92%, precision of 93.82%, F1-score of 93.15%, and overall accuracy of 94%.83%. This work showcases that, through integrating advanced image analysis and deep reinforcement learning, one can obtain a relatively high level of gruesomeness in tumor identification and delineation. Study [9] integrated deep and shallow feature extraction to distinguish brain tumors and forecast the 1p/19q co-deletion status of LGG tumors. Feature extraction was performed using pre-trained networks including AlexNet, ResNet-18, GoogLeNet, and ShuffleNet to extract the deep features, while a simple shallow network captured the low-level detail. These features were coupled, and the classification was done with the help of SVM as well as the k-NN classifiers. This common integration demonstrated that the fusion approach, when combined with the enlargement of the tumor region of interest (ROI), enhanced sensitivity by 11%. These results show that both informative and non-informative features are important for improving classification accuracy and, as a result, making a better diagnostic system. A study [10] looked into an algorithm that used deep CNNs and a nature-inspired ResNet152 transfer learning (TL) model to help find brain tumors and tell them apart. Preprocessing was done to the images to eliminate noise and to increase the quality of the acquired vectors using Otsu binarization, while feature extraction used GLCM methods. With an accuracy of 99%, the Covid-19 algorithm of weight tuning is then applied with ResNet152, which is recognized as a hybrid model. Compared to existing techniques, it achieves a low error rate of 57%. It illustrates the error rates and time complexity associated with brain tumor detection, and proposes more accurate and efficient solutions. These studies are groundbreaking in the classification of brain tumors, demonstrating a shift towards automating current classification systems and utilizing a variety of DL methods to enhance the precision and effectiveness of this diagnostic field.

The study [11] presents a general framework for brain tumor classification, localization, and segmentation using T1-weighted contrast-enhanced (T1W-CE) MRI images. Data splits into training, validation, and test parts and data augmentation techniques such as wavelet decomposition and geometrical transformations were used in this work, as were two DarkNet models (DarkNet-19 and DarkNet-53) that were pre-trained on other datasets. The DarkNet-53 model achieved unprecedented success in testing, achieving 98.54% accuracy, an area under curve (AUC) of 0.99, and a Dice index of 0.94 for tumor segmentation. This approach shows a remarkable improvement in the opportunity to perform tumor analysis through computer-aided systems as well as its applicability to clinical practice. DL using the EfficientNet family was proposed in study [12] as a way of improving the classification and detection of brain tumors. The approaches utilized a dataset of 3064 T1-weighted CE MRI images, along with pre-processing and data augmentation techniques, to improve the performance of the numerical models. Among all the models used, the most accurate model was the EfficientNetB3 model, reaching an accuracy of 99.69%, and it performs considerably better than many other existing state-of-the-art methods. To reach this conclusion, this study shows that engraving EfficientNet enabled faster, more reliable diagnosis, enhancing the early detection of brain tumors. In study [13], the researchers aimed to reduce the error rate and computational time in the development of a brain tumor detection approach, utilizing the deep CNN and the nature-inspired ResNet152 transfer learning (Hyb-DCNN-ResNet152 TL). The study included image denoising and image enhancement using Otsu binarization of images as well as the extraction of features using GLCM methods. The hybrid model, optimized using a Covid-19 optimization algorithm, showed striking accuracy rates that came within the range of 94.31% to 99.7% success rate and lower error compared to the existing techniques. This approach effectively reduces errors and enhances computational capabilities in the classification of brain tumors. In the study [14], the authors developed a new technique to classify three different types of brain tumors. They employed normalization, dense, speeded-up robust features, and gradient histogram methods to improve the quality of the MRI image and enhance the features for more detailed classification. The method adopted in the classification used support vector machine (SVM) with an accuracy of 90%. This work also demonstrates how feature enhancement techniques, when combined with reliable classification algorithms, enhance the diagnostic ability beyond what was previously possible. Finally, study [15] discussed brain tumor classification, which is a difficult task using a new technique, CNN with TL approaches. The study employed mixed CNN, which was augmented with a ResNet152 layer and optimized by the Covid-19 optimization algorithm. The approach achieved high accuracy rates, reaching up to 99 percent. Incidentally, these have been reported to be between 57% and significantly lower error rates than those of the conventional approaches. This study focuses on the enhanced capabilities of advanced neural network architectures and optimization algorithms, with the aim of reducing errors and enhancing classification ability. Collectively, these works present various state-of-the-art approaches to classifying brain tumors using DL frameworks, selecting and applying data augmentation strategies, and methods of feature selection and classification. Each study holds significance and relevance as it contributes to the ongoing refinement of diagnostic tools and methodologies, which in turn leads to enhanced efficiency in the identification and treatment of brain tumors. Table 1 shows the comparative analysis of the brain tumor classification studies in the literature.

Table 1. Comparative analysis of strengths and weaknesses of brain tumor classification studies

Strengths	Weaknesses	Citations
High classification accuracy (98.04%) across tumor types; Effective tumor localization and refinement using agglomerative clustering; Refined proposals increase accuracy.	Reliance on agglomerative clustering may introduce variability in tumor proposal accuracy; May require extensive computational resources for processing.	[6]
Impressive performance metrics (recall: 92.87%, precision: 93.82%, accuracy: 94.83%); Effective use of DenseNet121 for feature extraction; Data augmentation improves model robustness.	May not address variability in tumor characteristics or dataset bias; Focus on a single model architecture might limit flexibility.	[7]
Utilizes feature fusion of deep and shallow features; ROI expansion improves sensitivity (11.72% increase); Competitive results with ResNet-18.	ROI expansion may increase computational complexity; Shallow network design might not capture all relevant features.	[8]
High accuracy (99.60%) with DarkNet models; Effective use of data augmentation; Excellent performance in segmentation with a Dice index of 0.94.	Performance may be dataset-specific; DarkNet models' pre-training might limit generalizability to other datasets.	[9]
Outstanding performance with EfficientNetB3 (99.69% accuracy); Comprehensive preprocessing and augmentation techniques; High reliability for clinical settings.	May require extensive computational resources; Dependence on EfficientNet may limit exploration of other architectures.	[10]
High accuracy (98.54%) and AUC (0.99) with DarkNet models; Effective data augmentation and segmentation techniques; Demonstrates clinical applicability.	DarkNet models may not generalize well to other datasets; Dataset-specific performance may not reflect broader applicability.	[11]
Exceptional accuracy with EfficientNetB3 (99.69%); Advanced preprocessing and augmentation techniques; Significant improvement over state-of-the-art methods.	High computational requirements; EfficientNetB3's performance might not be as effective for all types of MRI datasets.	[12]
High accuracy (up to 99.57%) and low error rates; Effective use of hybrid CNN with ResNet152; Optimization through Covid-19 algorithm.	Potentially high computational cost; Hybrid model may be complex and harder to fine-tune.	[13]
Strong feature extraction using normalization and dense features; Good performance with SVM classification (90.27% accuracy); Surpasses previous methods.	May lack DL advantages; SVM may not be as robust as modern neural network approaches for all datasets.	[14]

2. ALGORITHM USED

This section highlights the various types of brain tumor classification algorithms based on machine learning (ML), DL, and TL.

2.1. Machine learning based classification

There had been progress in using ML, especially in the classification of brain tumors through the analysis of complex medical imaging data. Previous ML approaches, including SVMs, random forests, and k-NN, have been employed to classify brain tumors by learning from MR images extracted features [16]. These models require extensive preprocessing and non-automatic feature selection, which involves searching for specific features within the data sets to identify a specific tumor [17]. SVM as an algorithm that excels in working with high-dimensional space has been useful in classifying classes with well-separated margins, though the performance depends heavily on the feature space used. Random forests, based on decision trees, can handle large datasets and provide a quantitative measure of feature importance, making them useful in determining which aspects of the imaging data contribute to the classification [18]. However, these models can in fact become very intricate and less understandable when the number of trees carried is high. k-NN is a much simpler technique that can be perused for classifying tumors based on their majority of nearest neighbors in the feature space, which can be easily understood and implemented, particularly for small datasets. However, these traditional models have some drawbacks due to their reliance on manually designed features, which may not accurately reflect the actual patterns of brain tumors. To address this challenge, researchers have developed TL to fine-tune models trained on similar tasks or larger datasets for brain tumor classification. This approach helps in addressing the problem of restricted amounts of labeled data since it allows knowledge transfer across related domains, and thus the resulting model performs well.

2.2. Deep learning based classsification

DL has significantly impacted the medical field, particularly in the classification of features in brain tumor images [19] by automatically extracting features from the image data. Unlike standard ML models that involve handcrafted features, most DL models, particularly CNNs, learn hierarchical representations of the features from the raw data, making them ideal for image classification in general. Through layers of convolutional filters [20], [21]. CNNs aim to learn a set of spatial pyramids to model the hierarchies present in brain MRI scans, detecting edges, textures, and higher-level structures in the scanned image. These layers encapsulate the image features in a step-by-step manner so as to enable the network to learn complicated features that are relevant to tumor differentiation. By auto-learning from vast amounts of data, it has demonstrated state-of-the-art performance in brain tumor classification, outperforming the traditional approach in terms of precision and reliability. The other notable development in DL for brain tumor classification is TL, which makes use of pre-trained models on large datasets like ImageNet, for instance, VGGNet, ResNet, EfficientNet, and others in the classification task [22]. This method can be useful for further studies since, by tuning these models on the brain tumor datasets, they have shown high accuracy with a limited amount of labeled medical data. This makes the approach more suitable than most other training approaches since it not only shortens training time but also improves the model’s ability to generalize over different types of tumors and imaging scenarios. TL has been especially helpful in addressing the problem of scarce medical data, which remains a common issue in research in the sector. TL, whether through the use of pre-trained networks as feature substrates or feature tuning, has enabled DL structures to improve diagnostic performance from brain tumor images at a faster pace and with greater reliability. In addition, other technologies, including ensemble learning, data augmentation, and explicit attention mechanisms, have contributed positively to better classification of the brain tumor using DL models [23]. Ensemble learning, which involves using more than one model to make a prediction, increases robustness and accuracy, whereas data augmentation artificially increases the training data set by applying transforms like rotation and scaling, thereby reducing overfitting. In contrast, attention mechanisms bring the focus of the models on the parts of the image that are relevant, such as the tumor mass, and hence yield better classification results [24].

2.3. Transfer learning-based classification

Following section decsribe the in-depth TL based classification approaches.

2.3.1. Feature extarction

Feature extraction in brain tumor classification focuses on exploring necessary features from an MRI image with training of the pre-trained models for detecting significant features. This method leverages the fact that the models that are usually trained on large and diverse data can be used to convert raw MRI data into high-level features. Firstly, we choose a proper pre-trained model like VGG16 or ResNet since their feature extraction ability has been widely acknowledged. This process starts with feeding brain MRI images to this model to get feature maps or embeddings from the hidden layers. These feature representations, which contain the intricate details of even the internal structures of the images, are then used in the identification of the type of tumor through a second classifier that may be a SVM or a fully connected neural network. For instance, in the VGG16 brains, relevant features are extracted from brain MRI scans and logistic regression for a classifier, more precise ResNet high hierarchical features in addition to using other succeeding ML for classification. The major benefits of this approach include the fact that passing the features through layers reduces the amount of time that is taken in training since the important features can be obtained from the pre-trained feature maps. Additionally, the learned representations from such large datasets provide better classification accuracy for the particular task of tumor recognition. Nevertheless, what has been explained above about the feature extraction process is not free from certain limitations. The source of degeneration is rooted in the feature representation limitation of the pre-trained model, which may not contain sufficient features to represent different types of brain tumors [25], [26].

2.3.2. Fine tuning

Fine-tuning is an essential aspect of TL where the initial model is trained on a certain target dataset, like the images of brain tumors from MRI scans, to improve its performance [20] in the new task at hand [27]. The process starts with the ability to load a model that has been trained with a huge dataset of common objects, such as ImageNet, that provides the model with good features to start with. For this model to be applied in the classification of brain tumors, the early layers that generalize features such as edges and texture are left unfrozen in order to retain previously learned knowledge. To fine-tune the later layers of the model, as those layers are more precise in their nature and directly help us in extracting relevant features required for the classification [28]. This is corrected by retraining these layers using the brain tumor dataset in order to enable the model to identify specific features that are particularly related to differing types of tumors. In this phase, a smaller learning rate is used to avoid large changes to the pre-training weights as the model is finetuned for the new task while retaining the learned generalized features. Fine-tuning has become proven in a number of applications or uses. For instance, the ResNet50 model, while applied to classify brain MRI images to corresponding tumor types, has been shown to enjoy higher classification accuracy compared to other models by using a deep architecture and learned features to make the differential diagnosis [29]. In a similar manner, InceptionV3 has been applied to brain tumor datasets because, due to its highly stacked layers, it can capture multi-scale features. So, the advantages of fine-tuning are apparent in general with the improved aptitudes of the model to deliver the platform the benefit of specialized learning, where the basic motivation is to enable the model to specify in the salient characteristics of the brain tumors, which in effect enhances the productive classification [30]. Also, it is an effective utilization of labeled data as the framework avoids the requirement of large datasets, which is made possible by pre-trained models. Still, like any other process, fine-tuning comes with its own set of problems. Overfitting is a major problem facing the application of ML, especially when working with small data sets, since the model might end up learning the noise rather than capturing the underlying patterns. Furthermore, fine-tuning may be a computationally expensive process and needs a large amount of resources and time, especially when working with large models. Nevertheless, fine-tuning stays the main instrument in TL and helps to progress in the classification of brain tumors [31].

2.3.3. End to end training

End-to-end training means reusing pre-trained models by starting with a bank of weights learned by training on a large set of data collected from an image database to classify the novel set of brain tumors and fine-tuning this model on a new set of data [32]. This methodology combines the idea of using pre-trained weights acquired by learning from a large database, which incorporates the general concept of the images to learn from the new dataset, especially relating to brain tumors. The process starts with the loading of the base model and the initial weights, which include EfficientNet and DenseNet, among others, which are initially trained on datasets ImageNet [33]. After that, training is performed on the brain tumor dataset, and all weights of the model's layers are tuned to achieve the best accuracy in representing the new dataset. This all-encompassing training procedure has the advantage of distillation from extensive pre-trained feature representations and accurate, downstream tweaked modifications. Sophisticated methods are then used to improve the training rates and quality and to guarantee convergence to the final solution. A case of utilizing EfficientNet in end-to-end learning shows it has certain benefits by optimizing the integration of pretrained data and specific task data acquired in the classification of brain tumors. Likewise, the DenseNet architecture improves on the ability of the network to classify the input image since, when trained end-to-end, it draws on pre-trained weights to update upon exposure to new data [34]. Training from end to end is computationally expensive and time-consuming, especially with elaborate models and databases.

2.3.4. Multi-modal transfer learning

Using information from different modes of imaging like MRI and CT scans, multi-modal TL improves the identification of brain tumors from TL, which is capable of functioning across the different data sets [35]. Figure 1 shows the TL model approach. TL models leverage the knowledge gained by a model from pre-training on a large dataset and transfer this to a similar task with limited data, thus allowing faster convergence and improved performance. By reusing the learned features, TL minimizes the need for extensive training on smaller datasets and hence is of very high value in specialized applications such as medical image classification [36].

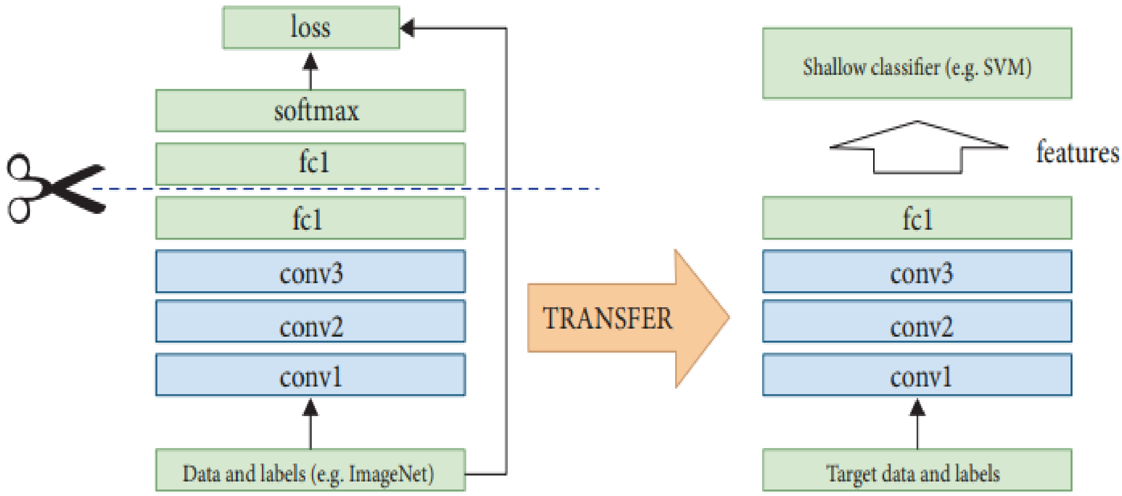

Figure 1. Transfer learning models [37]

This approach is meant to enhance the model's stability and performance through the aggregation of synergistic information from different sources. Data integration comes first, where two sets of images, MRI and CT scans, are fused to obtain a more improved set of data. This integration of the data from the two modalities may allow for a better description of the tumor in its entirety and may exhibit features that would not be observed when using only one method. Next, there is model selection, in which models appropriate for processing multimodal data are selected. These models, which are trained on a large and diverse dataset, are then fine-tuned for handling and learning from the integrated data. The training phase involves either fine-tuning or training the model on this enriched dataset, enabling it to function as a classification model that classifies the various types of information it receives. Some of the examples of this approach are MRI and CT scans, where the information of both modalities in training models works better in tumor classification than the utilization of single modality information. The advantages of multi-modal TL are significant: in addition to improving the model's accuracy, the utilization of multiple data sets enables the model to analyze many aspects of tumors, which would otherwise not be possible if only dealing with one data set [38]. This improves the stability of the model by enabling the proposed model to deliver accurate diagnostics, irrespective of the data type under analysis. However, there are certain drawbacks that cannot be left unnoticed. Inter-modality data compatibility: relating to data from different modalities at different formats and/or resolutions, the problem can be quite complex, especially since analytics has to merge the data together into one meaningful format to be exploited. Further, the multi-modal data are much more complex to manage and process as compared against the single type of data, as it demands much more resources and better approaches to handle all the gathered varieties of information. However, research shows that multi-modal TL significantly advances the field of brain tumor classification by harnessing the advantages of imaging modalities to create more accurate and reliable diagnostic models.

2.4. Comparartive analysis of the brain tumor classification algorithms

This Table 2 shows the comparative analyis of the each methodology, emphasizing the appropriateness of TL in areas such as brain tumor classification, where annotated medical data is frequently scarce.

Table 2. Comaparative analysis for the ML, DL, and TL for brain tumor classification

Parameter	ML	DL	TL	Citations
Data dependency	Requires feature engineering; small to medium-sized datasets are often sufficient.	High dependency on large datasets to automatically learn features.	Reduces dependency on large datasets by leveraging pre-trained models.	[29], [30]
Feature extraction	Manual feature extraction; requires domain expertise.	Automated feature extraction through hierarchical layers of the network.	Utilizes features learned by pre-trained models from large datasets, minimizing the need for manual extraction.	[32], [33]
Model complexity	Typically, lower complexity (SVM, decision trees).	High complexity (CNNs, RNNs), often involving millions of parameters.	Moderate complexity; builds on pre-trained networks like VGG, ResNet, Inception, etc.	[25], [42]
Training time	Shorter training time, especially with smaller datasets.	Long training time due to the large number of parameters and deep layers.	Significantly reduced training time as only the final layers or specific parts of the model are fine-tuned.	[17]
Performance on small datasets	Tends to perform well with tailored feature extraction.	Performs poorly unless augmented with synthetic data.	Superior performance by transferring learned features, fine-tuning models for small, domain-specific datasets.	[26], [43]
Accuracy	Moderate accuracy, depends heavily on feature engineering quality.	High accuracy when trained on large, diverse datasets.	Very high accuracy, especially in medical imaging tasks, as it benefits from both deep features and domain-specific tuning.	[29]
Computational resources	Requires moderate computational power.	High computational demand for training large models from scratch.	Moderate, since pre-trained models reduce the computational load.	[31], [32]
Interpretability	Relatively easier to interpret models (e.g., decision trees, SVM).	Harder to interpret due to deep layers and complex representations.	Moderate interpretability; features are pre-learned, but some layers can be fine-tuned for task-specific understanding.	[31], [32]
Generalization	Tends to overfit on small datasets without robust regularization techniques.	Strong generalization when trained on large datasets, but risks overfitting on small datasets.	Strong generalization; balances between large-scale pre-trained models and task-specific fine-tuning.	[36]
Examples of techniques/models	SVM, random forest, k-NN, Naive Bayes.	CNNs, recurrent neural networks (RNNs).	VGG16, ResNet, InceptionNet, EfficientNet with fine-tuning or end-to-end training.	[31], [29]

3. METHODS

This section describes the research methods using pre-trained models for brain tumor classification.

3.1. VGGNet

VGGNet is yet another DL architecture developed by the Visual Geometry Group from Oxford University [38], it has gained a lot of popularity in many image classification tasks, such as the medical imaging modality like brain tumor classification. There are three features in VGGNet: The neural network's rather simple structure suggests that deep convolutional layers, arranged one after the other, build the neural network; each layer uses three filters and ReLU activation. This approach allows for the enhancement of network features, from simple features like edges in the images to high-level abstract aspects. The network's variants are VGG16 and VGG19, and their names are associated with the number of layers: 16 and 19 correspondingly. Nevertheless, the deep nature of VGGNet's architecture aids in the extraction of intricate spatial hierarchies, making it one of the most effective existing approaches for image classification, similar to ImageNet. The authors note that one of its major disadvantages is the high computational and memory complexity given by a deep structure and many parameters [39]. This has led to the widespread use of VGGNet in medical image contexts, particularly for brain tumor classification. TL allows for the modification of pre-trained models like VGGNet and VGG16 to classify tumors using MRI data from datasets like ImageNet. In this setting, the initial layers of convolution first extract low-level features common to all the images, and then optimize the other layers to detect tumor-specific features. In this specific field, the application of VGGNet proves advantageous, as its design allows for the extraction and depiction of minute details in images, a feature that significantly aids in distinguishing between gliomas and meningiomas.

3.2. ResNet

Microsoft Research proposed the residual network (ResNet) and published 'Deep Residual Nets for Image Recognition', which significantly expanded the potential of DL by resolving the inherent vanishing gradient problem in training extremely deep neural networks [40]. The key feature of ResNet is its residual learning, where the concept of shortcut connections, also known as "skip connections," allows the network to traverse one or more layers at a time. This design allows for the training of networks that contain hundreds and possibly thousands of layers without experiencing the earlier cases of degradation in the performance of deep architectures. ResNet introduced several types of architectures: ResNet18, ResNet34, ResNet50, and ResNet101, where the number symbolizes the depth of the network. The deeper networks, such as ResNet50 and ResNet101, are more appropriate for such tasks because each layer is able to learn an abstract representation of the input image [41]. Nowadays, ResNet has achieved significant success in benchmarks like ImageNet, surpassing even its superior previous model, VGGNet. In the medical imaging sector, ResNet has transformed into a robust tool when it comes to tasks such as the classification of brain tumors [42]. TL saves researchers time and resources by enabling them to utilize large pre-trained models like ResNet from ImageNet and refine them on a smaller dataset of MRI brain scans, for instance. Because ResNet has residual connections, it is possible to get high-level and multi-level feature representations of the shape, texture, and edges of tumors. This makes ResNet a good tool for finding and classifying brain tumors. Additionally, ResNet possesses a robust feature extraction capability, rendering it ideal for integration into multi-level systems, allowing for the subsequent application of other techniques such as segmentation or alternative classifier architectures. Furthermore, studies have shown the model's usefulness not only in classification but also in tumor segmentation, where precise tumor margin delineation is crucial for treatment planning.

3.3. Inception network

The inception network called GoogLeNet was unveiled by Google in the ILSVRC 2014 competition, which changed the way how to design an efficient DL network. The Inception module is the most innovative part of this network. It combines multiple scale feature maps through the same layer by using convolution and max pooling with filters of different sizes (1×1, 3×3, 5×5). This method of extracting multi-scaled features in a multi-branch manner is efficient for computation and captures all types of features, from the first level to the second level patterns of the input image. Another significant contribution to the Inception architecture is the authors' use of 1×1 convolutions to reduce computational complexity, resulting in a decrease in the number of parameters without compromising accuracy. In this context, the network has undergone numerous iterations such as Inception-v3 and Inception-v4, incorporating minor modifications to the original design, such as the addition of new, more efficient layers and improved optimization techniques [43]. The network's extent and connectivity allow it to capture high-level simplistic features of images, and its hierarchical structure makes the model highly useful for image classification. In medical imaging, application of the Inception network has been particularly important in tasks such as classifying or segmenting brain tumors. That is why TL has made it possible to fine-tune Inception models, for example, Inception-v3, for medical tasks with the help of fewer samples, MRIs, or CT scans of brain tumors [44]. The network's ability to extract features at multiple scales is especially beneficial in medical applications such as image diagnostics, in which tumors may be of radically different dimensions. The Inception brooks of the network efficiently capture these variations, enabling accurate identification and classification of tumors. For instance, inception networks can distinguish between different types of brain tumors such as gliomas and menningiomas, which share many similarities but only slightly differ in their architectural and textural features across certain scales and multiscale networks.

3.4. EffiecientNet

The new model that Google created is called EfficientNet. It is the next step in the development of CNN architectures and makes the model much better at finding the best balance between accuracy and net computational cost. The primary improvement of the EfficientNet model is that it uses compound scaling, which means that one scales depth, width, and resolution at once. The main feature that differentiates EfficientNet from the traditional models that are scaled along one of the dimensions is that EfficientNet scales all three dimensions of the model proportionally, which allows to increase the model's efficiency while increasing its performance. By using this approach, we can create models that are significantly smaller and faster than some of the existing architectures, such as ResNet and inception. The efficient family contains the networks of B0, B1, B2, B3, B4, B5, B6, and B7, where the number after the letter B represents the power and size of the network [39]. This efficiency comes from mobile inverted bottleneck convolution (MBConv) and squeeze-and-excitation networks (SE blocks) that add further enhancement in computational utilization. This architecture not only applies to general image classification but is also especially useful for those applications that require high accuracy but can be computed in a limited way. Among the applications of medical imaging, it has been found valuable in areas such as brain tumor classification and segmentation. Given the small datasets and limited computational power, this suggests that DeepCT can scale particularly well for medical applications [45]. On the other hand, TL schemes can fine-tune EfficientNet model training using smaller medical imaging sets like MRIs of brain tumors. MRI images available in the dataset are preprocessed as shown in Figure 2. Due to the compound scaling of EfficientNet, it is capable of identifying small details of tumors, such as their shapes, texture, and contrast, which enhances its diagnostic ability. Researchers discovered that EfficientNet outperforms other architectures, specifically VGGNet and ResNet, in accurately classifying brain tumors such as gliomas, meningiomas, and pituitary tumors, by several percent.

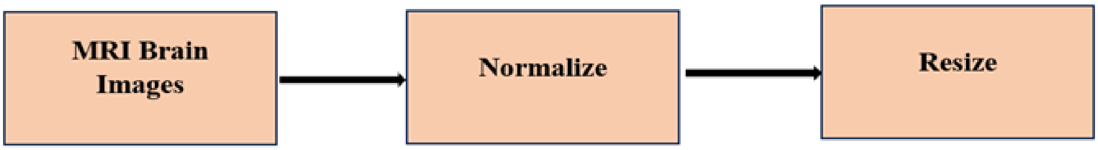

Figure 2. Steps for MRI results dataset by [46]

3.5. Comparative analysis of the pre-trained models for brain tumor classification

With the rapid development of image processing and artificial intelligence, the door has been thrown wide open to various automated systems for the classification of brain tumors. Thus, the requirement to assist the radiologist in diagnosis is useful in much faster and accurate manner. Techniques such as VGG16, ResNet, InceptionNet, and EfficientNet have emerged as some of the strong deep models for image recognition tasks. Table 3 shows the Comparison of the most popular pre-trained brain tumor classification models on architecture, complexity, accuracy, transferability, and small dataset performance.

Table 3. Comaparative analysis of the pretrained models

Model name	Architecture	Model complexity	Performance on small datasets	Accuracy in brain tumor classification	Citations
VGG16	16-layer deep CNN with 3×3 convolution filters.	Moderate; 138 million parameters.	Performs well with fine-tuning, but requires data augmentation.	High accuracy when fine-tuned for medical imaging tasks.	[39], [47]
ResNet	Residual Network with skip connections to avoid vanishing gradients (ResNet-50, ResNet-101).	High; 25-44 million parameters (ResNet-50/101).	Strong performance on small datasets with fine-tuning.	High; consistently performs well on medical image classification.	[41], [48], [49]
Inception Network	Inception modules with multiple convolution filters at different sizes.	Moderate to high; ~23 million parameters (InceptionV3).	Good performance on small datasets with TL and augmentation.	High; performs well when pre-trained on ImageNet and fine-tuned for brain tumor classification.	[44], [49], [50]
EfficientNet	Scalable CNN that balances depth, width, and resolution.	High efficiency; fewer parameters than ResNet, but strong performance (~5.3-19 million parameters).	Excellent; designed for efficiency and scales well on smaller datasets.	High; often outperforms other models in brain tumor classification tasks.	[45], [46]

From Table 2, it is analyzed that VGG16's simplicity and feature extraction are offset by its memory utilization and lengthy inference times. ResNet uses residual connections to train deeper networks, yielding excellent accuracy but increasing computing load. The inception network performs well on small datasets for multi-scale feature extraction, but its complexity makes fine-tuning difficult. Finally, EfficientNet balances accuracy and computing efficiency, often outperforming brain tumor classification tests, but it may require careful tuning. These models demonstrate the evolution of DL architectures in medical imaging, progressively improving diagnostic capabilities.

4. RESULTS AND DISCUSSIONS

Recent studies of the identification of brain tumors through TL suggest that the level of accuracy and propensity of diagnosing brain tumors has been enhanced by imaging techniques of various types. The use of CNNs like ResNet, VGGNet, and DenseNet, among other DL models, has proven very efficient in the classification of brain tumors from MRI and CT images. Through TL, these techniques can fine-tune on such small datasets that belong to a particular domain, and they can achieve good classification accuracies, which are normally higher than 90%. This approach not only improves the prediction of models when big labeled data sets are rare but also cuts the amount of computation and time taken into half. These models have been found to perform well for characterization of various tumor types and subtypes with higher accuracy than traditional ML models, which require feature engineering. Additional treatments like data augmentation, the use of attention, and ensemble learning provide an additional guarantee for the reliability and versatility of these models.

Data augmentation resolves the problem of small training data by creating more data while attention increases the models' focus on specific tumor parts, hence increasing the classification performance. First, ensemble learning applies several models and refines their outputs to enhance the accuracy of the model predictions. However, there are still some issues; the DL models are computation-intensive, and in clinical practice, we often require an explanation of the output models. The application of TL with MRI and CT images has solved the challenges, improved the brain tumor classification, and contributed to more accurate, efficient, and scalable solutions for the patients' management and treatment strategies.

5. CONCLUSION

The TL approach to the brain tumor classification has significantly improved the diagnostic accuracy across MRI and CT medical images. Authoritatively, it has been noted that fine-tuned through TL, DL models like CNN, ResNet, VGGNet, and DenseNet had passed the 90% accuracy rate in classifying the brain tumors. The advancement of this technology meets significant problems of the field, such as the requirement of large labeled datasets of examples and the time-consuming computation that arises when retraining models from the primary are required. With the help of such tactics as data augmentation and features like attention, these models enhance the classification accuracy and make the models more robust and useful in clinical practice and further research. However, there are several issues that remain with DL models, including the time consumption in computation of high-complexity models, model explanation or understanding, and patient privacy.

Potential improvement of the algorithms, increasing the interpretability of these models, and the integration of these sophisticated systems in clinical practice for daily use in the future. TL, DL, and other advancements in the field continue to see enhancements; hence, the future holds better solutions to accurately diagnose brain tumors. These technologies, currently in developmental phases, possess the capacity to revolutionize medical imaging, thereby enhancing patient outcomes through improved diagnostic capabilities and more precise treatment decisions.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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