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A review on detecting brain tumors using deep learning and magnetic resonance images

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ABSTRACT

Early detection and treatment in the medical field offer a critical opportunity to survive people. However, the brain has a significant role in human life as it handles most human body activities. Accurate diagnosis of brain tumors dramatically helps speed up the patient's recovery and the cost of treatment. Magnetic resonance imaging (MRI) is a commonly used technique due to the massive progress of artificial intelligence in medicine, machine learning, and recently, deep learning has shown significant results in detecting brain tumors. This review paper is a comprehensive article suitable as a starting point for researchers to demonstrate essential aspects of using deep learning in diagnosing brain tumors. More specifically, it has been restricted to only detecting brain tumors (binary classification as normal or tumor) using MRI datasets in 2020 and 2021. In addition, the paper presents the frequently used datasets, convolutional neural network architectures (standard and designed), and transfer learning techniques. The crucial limitations of applying the deep learning approach, including a lack of datasets, overfitting, and vanishing gradient problems, are also discussed. Finally, alternative solutions for these limitations are obtained.

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1. INTRODUCTION

Human cells usually grow controlled, creating new cells to replace damaged or old ones. In contrast, abnormal cells grow due to uncontrolled cell division, and abnormal tissue is created, called a tumor. Tumor cells reproduce uncontrollably for reasons not entirely known. A brain tumor is an example of such abnormal cells, and it could be primary (starts initially in the brain) or secondary (starts in another area and spreads to the brain). Options to treat the tumor vary based on its location, size, and type. Additional factors include the patient medical health, his/her age, and whether the tumor has spread. Usually, a primary brain tumor does not spread outside the brain. It could be benign or malignant. Benign brain tumors rarely spread, have distinct boundaries, and grow slowly. These tumors can be considered life-threatening, although they consist of benign cells and are found in a vital area. Conversely, malignant brain tumors spread to nearby brain areas have irregular boundaries and overgrowth. These tumors do not spread to the organs or spinal cord outside the brain and disagree with the cancer definition. Thus, it is not correct to name them brain cancers. Whatever the type of brain tumor is, all are potentially dangerous because the people's death rate having brain tumors is considerably high. For life-saving and better treatment, early detection of brain tumors becomes very important [1].

Experts commonly use magnetic resonance imaging (MRI) and computed tomography (CT) to produce well-detailed brain structure images. The suspected brain tissue may need a surgical biopsy by specialists for a detailed diagnosis to obtain more information about the tumor. In particular, oncologists usually evaluate brain tumors using the scan images gathered from medical imaging systems, like positron emission tomography (PET), MRI, and CT. Recently, these systems showed significant enhancements in image resolution and contrast. This progress allows the specialists to recognize even miniature tissues to achieve better diagnostic accuracy [2]. MRI obtained the most effective imaging technique for looking at the nervous system and soft tissues. It does not utilize the x-ray radiation that can be harmful and not like CT scans [3].

Artificial intelligence (AI) has recently emerged as a massive revolution in engineering technologies, especially in computer vision. The benefits of these technologies are combined with the images gathered from various imaging systems to effectively enhance the detection accuracy of the brain tumor. Computer-aided diagnosis (CAD) systems are developed as a result of integrating AI with these imaging systems to support specialists in improving the early detection accuracy of brain tumors. Artificial neural networks (ANNs), machine learning algorithms, and deep learning models are AI tools used to detect and classify brain tumors [4]. ANN is the first concept of introducing artificial intelligence in different sectors of our life, including the medical sector. Then, it extended to include machine and deep learning.

In the ANN approach, Abdalla and Esmail [5] applied a set of techniques to extract features calculated using the spatial gray level dependency (SGLD) matrix-based Haralick's feature equations. An automated supervised learning method with a feedforward backpropagation neural network was used for the classifying stage. They have achieved an accuracy of 99%. Josephine and Murugan [6] introduced a feedforward neural network to classify brain tumors into benign and malignant using different feature algorithms. These algorithms include an algorithm that assigns the features as many pixel counts. Another algorithm is applied to eliminate the feature size based on essential features depending on the brain anatomy and the tumor. The dataset consists of 30 images, and the 2D spatial domain signals were analyzed using the Gabor filter. The algorithm achieved an accuracy of 96%. Moreover, different fiction strategies of computer vision are applied to enhance images, segment images, and filter [7], or different machine learning algorithms are combined for classifying brain tumors [8].

Machine learning (ML) algorithms are generally categorized into three fields based on their learning: supervised, semi-supervised, and unsupervised [9]. Supervised learning uses feedback theory to determine the optimal parameter values. It is widely used in different medical and non-medical applications. Conversely, unsupervised learning does not use feedback in its weight updating. Semi-supervised learning is an approach between supervised and unsupervised learning approaches. In particular, a collection of limited labeled instances with abundant unlabeled ones is utilized for training a model in a semi-supervised approach [10]. Support vector machine (SVM) is commonly employed among various machine learning algorithms due to its accuracy and ease of implementation. Recently, machine learning algorithms have been combined with deep learning models to achieve better detecting and diagnosing accuracy [11], [12].

The last AI approach represents the recent type of ML, named the deep learning (DL) approach. It is based on in-depth learning analysis [13]. The convolutional neural network (CNN) is widely used among other DL architectures because it can execute complex operations based on convolutional kernels [14]. In particular, the CNN structure is an arrangement of feed-forward layers, mainly including convolution, pooling, and fully connected layers. The first two types are used for extracting features, while the third is used for classification [15]. Several CNN models have been released, like AlexNet, VGGNet, MobileNet, DenseNet, Inception, ResNet, and NASNet architecture [16]. Lastly, a new concept called transfer learning is applied in the DL approach to support solving various pattern problems based on a pre-trained CNN model. Such a model transfers knowledge to the model under design. This knowledge is typical features learned from the pre-trained model and can be applied to a different objective task [17]. Several models have been recently released using transfer learning with well-known CNN models like MobileNet, Xception, and ResNet [18].

This review paper is a comprehensive article suitable as a starting point for researchers to demonstrate essential aspects of using deep learning in diagnosing brain tumors. More specifically, it has been restricted to only detecting brain tumors (binary classification as normal or tumor) using MRI datasets in 2020 and 2021. The research before 2020 is covered by several published papers [19]–[21]. In contrast, the limited research during 2021 to diagnose brain tumors as binary classification rather than multi-classification leads to including the research of 2020. It should be noted that most research in 2021 is focused on segmentation and multi-class diagnosis. We think that accurate detection is a critical stage for multi-classifications and needs more investigations to achieve the highest detecting accuracy. Among these restrictions, the subsequent sections present datasets, data augmentation, CNN architectures (standard and designed), and transfer learning techniques frequently employed in the research. Moreover, the most limitations in applying the deep learning approach, including a lack of datasets, overfitting issues, and vanishing gradient problems, are also discussed. Finally, alternative solutions for each limitation are obtained.

2. DETECTING BRAIN TUMORS USING DEEP LEARNING

The general block diagram of a detecting brain tumor model consists of four main stages, as demonstrated in Figure 1. Data gathering is the first stage, where images are downloaded from online datasets or are collected and labeled manually, which is an effort and cost-effective process but becomes a state-of-the-date dataset. Preprocessing and data augmentation is the second stage, an optional stage based on the number of images in the dataset and its quality. Preprocessing includes resizing the image dimensions or formatting the image to suit the model used, while filtering is required for noisy images. Data augmentation includes cropping, mirroring, rotating, and flipping. It is required to enlarge the dataset, as DL is hungry for images. The DL model is the core of the detecting system, which can be a standard (famous) model, designed, or hybrid one. The model output is either normal or tumor (binary classification). The last stage is optional as an alternative solution to data augmentation to enhance the model performance.

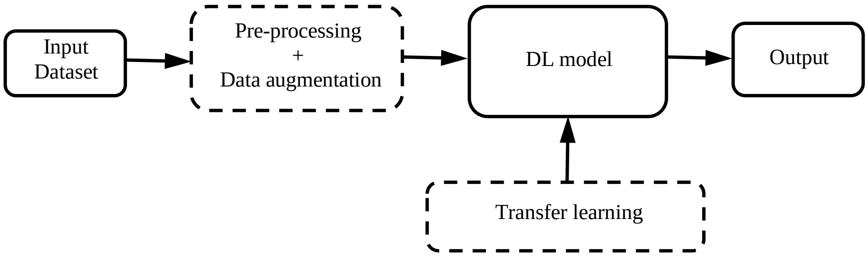

Figure 1. General DL-based brain tumor detection block diagram

2.1. Dataset

The data source has a major role in diagnosing various diseases [22]. According to their research, the researchers use colorful or grayscale 2D or 3D images to detect brain tumors. Filtering the acquired images from noise and distortions is important in obtaining better results [12]. High-quality annotations with large images are required to get favorable findings. In contrast, labeling many images is a critical challenge since annotations are cost-effective in both expertise and time [23]. In particular, deep learning needs a considerable dataset size to work perfectly [22]. In the following, a summarization of the most available brain tumor detection datasets from the Kaggle website and others is presented.

Starting with Brain MRI images for brain detection – version 1 developed by Chakrabarty [24], the dataset contains 253 images classified into two classes: normal and tumor. Hashan [25] presented the MRI Based brain tumor images – version 1, a dataset that contains two subfolders: one for normal and the other for tumor. The dataset consists of 400 images: 170 normal and 230 tumor images. Another dataset named BraTS 2019 [26] was introduced by Felix and has three folders (train, valid, and test) with a total of 3,006 images that are divided into only six images in the test folder, 200 images in the valid folder, and 2,800 images in the train folder. Note that all images have the form "*.jpg*" form.

Cheng [27] presented a Brain tumor dataset, Figshare with 3,064 T1-weighted contrast-enhanced images obtained from 233 patients. These images are categorized into three types of brain tumors: 1,426 glioma, 708 meningioma, and 930 pituitary images. This dataset is organized to work within the MATLAB environment, where the image format is of "*.mat*" form. In 2019, Sartaj [28] introduced a dataset called Brain tumor classification (MRI) – version 1 and updated it in 2020 (version 2); that has 3,264 images and is categorized into two main folders: training and testing. Both folders have four subfolders but with a different number of files (images). The training images are categorized into 395 normal, 826 glioma, 822 meningioma, and 827 pituitary tumors, while the testing images are: 105 normal, 100 glioma, 115 meningioma, and 74 pituitary. Note that all images have the "*.jpg*" format.

Br35H :: Brain tumor detection 2020 – version 12 [29] dataset developed by A. Hamada that contains more than 3,000 images. It is classified into normal and tumor classes and is mainly established for detecting brain tumors. Unfortunately, no details from the source are available. Lastly, the Brain tumor MRI dataset – version 1 [30] is presented by Nickparvar for multi-class diagnosing with 7,023 images. It comprises two main folders (training and testing) and four subfolders each. The training folder has 5,712 images (1,595 normal, 1,321 glioma, 1,339 meningioma, and 1,457 pituitary), while the testing folder has 1,311 images (405 normal, 300 glioma, 306 meningioma, and 300 pituitary). This dataset has a "*.jpg*" image format.

Table 1 lists the various MRI datasets from the Kaggle website for diagnosing brain tumors. Among these datasets, the Figshare dataset contributed the most to the research in 2020 and 2021, although it is typically created for multiple brain tumor classification [31]–[34]. Based on the model architecture, it obtained a high model accuracy (greater than 98%). For brain tumor binary classification, datasets [24], [25], [28] are used in research [35], [36] during the same period. From the GitHub website, a dataset of 2,065 images is also used in the research [36]. However, these works did not obtain a high accuracy (89 to 97%).

Table 1. MRI Brain tumor online datasets

Dataset Name	Source [Ref.]	Year (last updated)	Total number of images	Details
Brain MRI Image for Brain Tumor Detection – version 1	[24]	2019	253	98 normal and 155 tumors
MRI-Based Brain Tumor Images – version 1	[25]	2021	400	170 normal and 230 tumors
BraTS 2019	[26]	2019	3,006	1,503 normal and 1,503 tumors
Figshare	[27]	2017	3,064	1,426 gliomas, 708 meningiomas, and 930 pituitary
Brain tumor classification (MRI) – version 2	[28]	2020	3,264	500 normal, 926 gliomas, 937 meningiomas, and 901 pituitary
Br35H :: Brain tumor detection – version 12	[29]	2020	more than 3,000	at least 1,500 normal and 1,500 tumors
Brain Tumor MRI dataset – version 1	[30]	2021	7,023	2,000 normal, 1,621 glioma, 1,645 meningioma, and 1,757 pituitary

2.2. Data augmentation

In general, deep learning is hungry for data. One possible solution to increase the data is to apply data augmentation techniques. For any limited-dataset issue, these techniques are the data-space solutions. They significantly enhance the size and attributes of the training datasets. Data augmentation techniques include flipping, color space, cropping, rotation, translation, mirroring, noise injection, and cross-modality image generation [18]. From the previous section, all the brain tumor datasets have a shortage in their data, resulting in a low-performance accuracy [37]. Thus, the main goal of using data augmentation is to enhance performance accuracy and avoid overfitting problems [19]. Table 2 lists several types of research that used different data augmentation techniques for diagnosing brain tumors.

Table 2. Research that used data augmentation techniques

Source [Ref.]	Year	Dataset before augmentation	Dataset after augmentation	Augmentation
[38]	2021	3253	16263	Not mentioned
[39]	2021	3064	15320	Noise injection, Mirroring, Flipping, Rotation
[40]	2021	253	2530	Rotation, Shifting, Brightness, Flipping
[18]	2021	253	1516	Rotation, Shifting, Brightness
[41]	2021	400	1660	Rotation, Shifting, Sheering, Brightness, Flipping, Filling
[37]	2021	253	2065	Rotation

2.3. Standard (famous) CNN architectures

The model architecture is crucial in bettering the performance of various applications. Numerous CNN architectures have been released over the last ten years. Since 1989, CNN architecture has shown different modifications, such as architectural reforming, regularizing, and parameter optimizing. However, the crucial upgrade in CNN performance happened essentially due to the development of novel blocks and the reorganization of the processing unit. Notably, most of the developing blocks were implemented utilizing the network depth. This section reviews firstly the widely used CNN architectures, including AlexNet, VGG, GoogLeNet, Inception versions (v2, v3, and v4), ResNet, and DenseNet models, with their applications in detecting brain tumors. Then, the other developed models in 2020 and 2021 are also reviewed.

The winner of the most challenging competition for recognizing visual objects named ImageNet large-scale visual-recognition challenge (ILSVRC) was the AlexNet network [42]. Compared to the LeNet model [43], the AlexNe t[42] model is a wider and deeper CNN model. The model has seven convolutional layers (rather than five in LeNet), a ReLU activation function, and a softmax of 1000-way [19]. Cinar and Yildirim [44] proposed a hybrid CNN model to diagnose brain tumors using an online dataset of 253 images. They achieved an accuracy of 97.2%, but when they applied AlexNet to their dataset, they achieved 89.55%. Togacar *et al.* [45], in 2020, applied the feature selection method and the hyper-column technique with CNN to classify brain tumors. They used the same dataset (253 images) and applied data augmentation to equalize the normal images with the tumor ones. They have achieved an accuracy of 96.77%, while the AlexNet model obtained 92.47%. Thus, data augmentation increased the accuracy by 3% compared to the previous one. In a comparison study, Diker [46] employed three widely used pre-trained models (AlexNet, GoogLeNet, and ResNet-18). This study also used the same dataset. Among these models, AlexNet has achieved the highest accuracy of 96%. It can be concluded that pre-trained models can significantly enhance the overall model performance (including accuracy).

At the University of Oxford, Simonyan and Zisserman [47] introduced a CNN model called visual geometry group (VGG) in the ILSVRC competition [48]. It is one of the most attentional models in the competition and has achieved an accuracy of 92.7%. It is much deeper than AlexNet. VGG16 consists of 13 convolutions, 5 pooling, and 3 fully connected layers. VGG19 is a newer version of VGG16 with three additional convolutional layers. The VGG model is used in many works to diagnose brain tumors. Grampurohit *et al.* [49] presented a VGG16 model to achieve an accuracy of 91.9% using an online dataset of 253 images without applying preprocessing techniques or data augmentation. Sevli [50] uses three pre-trained models, including VGG16, ResNet 50, and Inception v3, to detect brain tumors with the same previous dataset (253 images). The VGG16 obtained the highest accuracy of 85.92% without data augmentation and 94.42% with data augmentation. The total number of images after augmentation was 302 images. Lastly, Siddique *et al.* [35] proposed a modified pre-trained VGG16 model by replacing the last max pooling layer with an average pooling one and freezing the central convolutional layers. The dataset is also the same dataset of 253 images. This model achieved an accuracy of 96%.

Another CNN standard model named GoogLeNet [51] is the first version of a so-called inception network and the winner of the ILSVRC 2014 competition [52] with a 6.67% error rate. It is thought to be the first application of modern CNN architecture, which is made up of more than just successive convolution and pooling layers. More specifically, it utilized the concept of the inception architecture by skipping connections to form mini-modules replicated all over the network. Compared to 60 million parameters used in AlexNet, these mini-modules drastically lowered the used parameters to a 9-fold reduction (roughly seven million parameters) in GoogleNet. In contrast, VGGNet utilized parameters approximately three times that of AlexNet [53]. Substituting the fully connected layer with an average pooling layer is another interesting feature that makes training much faster. However, Diker [46] presented a performance comparison of different DL models to classify brain MRI images. In this work, GoogLeNet comes in second place with an accuracy of 90.66 % after the winner AlexNet. In another study, Fuad *et al.* [54] also compared AlexNet and GoogleNet architectures using a dataset of 3,064 MRI images. Again, GoogLeNet has achieved an accuracy of 92% after AlexNet.

Looking for deeper CNN and free of vanishing gradient problems other than AlexNet and VGG is the residual network (ResNet) developed by Ghosal *et al.* [55]. It is the winner of ILSVRC 2015. The model initially consists of 34 layers and is modified up to 1,202 layers. Some versions include ResNet50, ResNet101, and ResNet152. The most widely used version is ResNet50, with 49 convolutional layers and a single fully connected layer. Using the bypass pathway concept in the ResNet models is a novel idea [56]. Its architecture uses batch normalization to enhance network performance. Deepa *et al.* [57] analyzed the performance of three ResNet versions: ResNet50, -101, and -152. Their dataset consists of 11,722 images collected from the Oasis dataset and the BRATS2017 challenge. It has 3,250 normal images and 8,472 tumor ones. This dataset is randomly divided into 80% for training, 10% for validating, and 10% for testing. They achieved an accuracy of 89.3%, 92.2%, and 93.8% for the models ResNet50, -101, and -152, respectively. In a similar work to [50] with the same dataset, Saxena *et al.* [58] achieved the highest accuracy of 95% with ResNet50, while their VGG16 model achieved only 90% accuracy, including data augmentation. Lastly, Kumar *et al.* [59] applied a modified ResNet50 to achieve an accuracy of 97.48% with data augmentation and 97.08% without augmentation. The main modification was replacing the max-pooling layer with a global average pooling one to answer overfitting and vanishing gradient problems. They used an online dataset (Figshare [27]) of 3,064 images.

However, the ResNet architecture showed some drawbacks. For instance, ResNet has many weights because all layers have separated weight sets. DenseNet architecture is introduced to solve this issue and other drawbacks by employing the concept of cross-layer connectivity, where each layer is connected to the whole network's layers. Thus, all feature maps of the preceding layers become inputs to the following layers. More specifically, there are *l* connections between any two adjacent layers in traditional CNNs, while there are $\frac{l(l+1)}{2}$ connections in the DenseNet model. The architecture of the DenseNet is composed of four blocks, but each block has a different number of layers. For instance, DenseNet-121 has (6, 12, 24, 16) layers, DenseNet-169 has (6, 12, 32, 32) layers, and DenseNet-201 has [6, 12, 48, 32] layers [60]. Noreen *et al.* [61] presented a model composed of Inception v3 and DenseNet201. They performed two scenarios in operation. The first scenario used the Inception v3 model to extract features, while the second used the pre-trained DenseNet201 for feature extraction. The feature extracted are then concatenated for diagnosing brain tumors. They achieved 99.34% and 99.51% accuracy for the two scenarios. The dataset consists of 3,064 T1-weighted contrast images developed by Cheng [27]. Table 3 summarizes the research using the four widely used CNN models for detecting brain tumors.

Table 3. Summarized research using four widely used CNNs

CNN model	Reference	Model type	Accuracy
AlexNet	[44]	AlexNet	89.55%
	[45]	AlexNet	90.32%
		AlexNet+ Hyper-column	92.47%
	[46]	Pre-trained AlexNet	96%
VGG	[49]	VGG 16from scratch	91.9%
	[50]	pre-trained VGG16	94.42%
	[35]	DCNN-based pre-trained VGG16	96%
GoogleNet	[46]	pre-trained GoogleNet	90.66 %
	[54]	GoogleNet with TL	92%
ResNet	[57]	ResNet152	93.8%
	[58]	Pre-trained Resnet50	95%
	[59]	ResNet-50 + Global Average Pooling	97.48%
DenseNet	[61]	Incept ion v3+DenseNet201	99.51%

2.4. Designed CNN architectures

Due to imprecise findings in detecting brain tumors with a significant variation in decision–making, numerous people were passed away in recent years [12]. Thus, several works have been released [62]. Ghosal *et al.* [55] proposed a ResNet101 model as the base model and combined it with squeeze-and-excitation (SE) blocks [63] to form the SE-ResNet101 model. They used a private dataset of 3,049 images (including 1,426 Glioma tumors, 780 Meningioma tumors, and 915 Pituitary tumors) collected from two hospitals in China. They also applied data augmentation to enhance the model performance and obtained accuracies of 93.83% and 89.93% with and without data augmentation, respectively. The total image becomes 7,721 images after data augmentation.

In 2020, Bhanothu *et al.* [64] introduced a faster region-based CNN model that comprised three main blocks, including R-CNN, region of interest (RoI), and region proposal network (RPN). The model base is VGG16, while the dataset is available online and consists of 3,065 images. They obtained an average precision of 77.6%. Rumala *et al.* [65] presented a deep CNN implemented to classify brain MR Images into normal and abnormal classes. The CNN architecture was evaluated using different epoch numbers and four activation functions (ReLU, Leaky ReLU, ELU, and Tanh). The best classifier performance was obtained using the exponential linear unit (ELU) activation function at epoch 50 to get an accuracy of 99.12%.

Kesav and Jibukumar [31] introduced a novel low-complex architecture consisting of two-channel CNN and R-CNN models. The two-channel CNN was applied first for classifying the MRI images into healthy and Glioma tumors. Then, the R-CNN model is employed for detecting the tumor regions from the Glioma tumor images. The detected regions are then bounded with bounding boxes. The authors released that this approach obtained a shorter execution time than standard CNNs like AlexNet, VGG, and ResNet. They utilized two datasets available to the public: one from Kaggle (2020) and the other from Figshare [27].

Brindha *et al.* [66] implemented ANN and CNN models to detect brain tumors. The ANN model consists of seven layers. A flattened layer is used as the first layer to convert the 2D images into a 1D array. Dense layers with ReLU activation function are used in the successive five layers as hidden layers, while the seventh layer is also dense with a sigmoid activation function for classification. In contrast, the CNN model consists of five convolutional blocks (each block consists of three layers: convolution, max pooling, and dropout layers), a flattened layer, and a fully connected layer. They have achieved 65.21% and 89% accuracy for the ANN and CNN models. The dataset was gathered from the GitHub website with a total of 2,065 images: 980 normal and 1,085 tumors.

Kibriya *et al.* [39] applied two DL models: GoogLeNet and ResNet-18, to diagnose multi-class brain tumors. They also applied an SVM classifier instead the fully connected layer to achieve better accuracy. They used an online dataset from the Kaggle website with 3,064 images and applied data augmentation to enlarge the dataset five times. The total number of images becomes 15,320 images. They obtained accuracies of 97.4%, 97.6%, 97.8%, and 98% for GoogLeNet, GoogLeNet+SVM, ResNet-18, and ResNet-18+SVM. It is obtained that the SVM classifier does not significantly improve the accuracy (just 0.2%), while the data augmentation plays the main role in bettering the accuracy.

Lastly, Methil [67] used a pre-trained ResNet101v2 model as a base model and performed various image preprocessing methods like histogram equalization, global thresholding, median blur, dilation, and others). Next, transfer learning is also applied to the base model. The resultant model has achieved an accuracy of 95%. The dataset combined two online datasets with a total of 4,222 images. Alternatively, Sandhiya *et al*. [68] utilized a faster R-CNN for multi-class brain tumor diagnosis and a DCGAN for preprocessing (data augmentation) by creating fake images as actual ones to mislead the classifier. This technique enlarges the dataset for better model performance and accuracy. The region proposal time using the faster R-CNN was 10 ms, which is suitable for real-time applications. Their model obtained a classification accuracy of 89.9%. Table 4 lists the literature works using designed CNN models.

Table 4. Summarized works using designed CNN models

Year	Source [Ref.]	Designed CNN model	Description	Dataset	Accuracy
2019	[55]	SE-ResNet101	Squeeze and extraction technique is combined with ResNet101, Intensity normalization and zero-centering are applied as a pre-processing step	Figshare [21]	93.83%
2020	[64]	VGG16 + R-CNN	VGG16 is the base model with a faster R-CNN algorithm, The optimal boundary box is generated using the RPN method	Figshare [21]	Average precision 77.6%
2020	[65]	CNN	ELU activation function is applied with a CNN model	The cancer imaging archive (TCIA), http://www.med.harvard.edu/AANLIB	99.12%
2021	[31]	CNN + R-CNN	Two-channel CNN for binary classification, Its features with R-CNN for multi-classification	Figshare [21]	98.21% and 98.83% (Binary and multi-classification)
2021	[66]	CNN + ANN	CNN as a base model with ANN as a classifier	GitHub website	89%
2021	[39]	ResNet18 and GoogLeNet	Two models: ResNet18 and GoogLeNet were used with the SVM classifier	Figshare [21]	ResNet18: 98% GoogLeNet: 97.6%
2021	[67]	ResNet101	Pre-trained CNN with ResNet101-v2, Several preprocessing techniques were applied	https://www.kaggle.com/jakeshbohaju/brain-tumor https://www.kaggle.com/navoneel/brain-mri-images-for-brain-tumor-detection	95%
2021	[68]	R-CNN	DCGAN preprocessing technique is applied	Not mentioned	89.8%

2.5. Transfer learning

An alternative solution to the problem of undersized datasets rather than data augmentation is transfer learning (TL). It is much more effective in considering the shortage of training data. TL mechanism includes training a CNN model with a sizeable volume of data [69]. A proper way to clarify TL is by explaining the relationship between the teacher and the student. Initially, detailed information on the subject is collected. Then, the teacher conveys the information in several lectures as a "course" to be transferred later to the student. Simply, the teacher (expert) transfers the information (knowledge) to the student (learner) [70].

Similarly, a deep learning model is trained with a huge amount of data and learns the weights and the bias. This information (weights and bias) is then transferred to another model for retraining and testing. Therefore, the new model can start with pre-trained weights rather than training from scratch. Two crucial benefits of training a new model with pre-trained weights include helping the model's generalization and speeding up convergence [71]. For example, Yang *et al.* [72] applied TL to AlexNet and GoogLeNet models to improve their performance. The result showed that AlexNet performance closely approaches GoogLeNet performance. Deepak and Ameer [73] employed a pre-trained GoogLeNet model to solve the problem of their limited dataset (Figshare [27]). They released that TL is a powerful technique for limited datasets cases. The proposed system has achieved a mean classification accuracy of 98%, beating the up-to-date techniques.

In contrast, Noreen *et al.* [61] presented a study to prove that different blocks' concatenated features can attain better performance than a singular block. They utilized two pre-trained CNN models in two scenarios: Inception-v3 and DensNet201. The first scenario used different pre-trained inception-v3 models to extract features. Then, these features are concatenated for classification. The second scenario used DensNet201 models instead. They released that the DensNet201 and Inception-v3 scenarios have achieved accuracies of 99.51% and 99.34%, respectively.

Chelghoum *et al.* [74] presented an interesting study that utilized nine pre-trained networks, which are AlexNet, GoogLeNet, VGG (16 and 19), ResNet (-18, -50, -101, and –inceptionv2), and SENet for TL. Their dataset (Figshare) has 3064 images [27]. Classification accuracy, training time, and overfitting are considered factors. They released that TL improves classification accuracy and training time and avoids overfitting. In addition, they have achieved better accuracy of 98.71% than the work of Deepak and Ameer [73]. A similar work uses only three pre-trained standard CNN models: VGG16, Inception-v3, and ResNet-50 as feature extractors [58]. The authors obtained that the ResNet-50 model has the highest accuracy and F1-score with 95% and 0.952. The VGG16 model comes in second place, whereas the Inception-v3 model showed an overfitting problem.

Shoaib *et al.* [36] presented four models to classify brain tumors. These models are a pre-trained inception-v3, a pre-trained InceptionResNet-v2, a designed from-scratch CNN-based, and a transfer learning model. Unfortunately, they did not describe the architecture of the transfer learning model, but it has achieved the highest accuracy of 93.1%. The second was the designed CNN model with an accuracy of 91.24%. Lastly, Bayoumi *et al.* [17] introduced five-layer modifications with parameters tuning to five pre-trained standard CNN models, including AlexNet, VGG16, GoogLeNet, ResNet-50, and Inception-v3, to produce new CNN architectures. These modifications start with replacing the last layer with a different one. Then, the last two layers, up to five layers. They used two datasets; the first has 349 images with 109 normal and 240 tumors, while the second contains 120 images with 60 normal and 60 tumors. They released that transfer learning has a highly effective role in obtaining very successful performance, and the best accuracy, sensitivity, and specificity achieved was 100% for all of them.

Lastly, Abbood *et al.* [11] implemented three pre-trained deep learning schemes (DLS): VGG16, VGG19, and ResNet50, with different types of classifiers, including softmax, SVM-RBF, and SVM-Cubic. They have achieved the best accuracy of 95.8% with VGG16+SVM-RBF, 96% with VGG19+SVM-Cubic, and 92.6% with ResNet50+SVM-RBF. Table 5 summarizes the research using transfer learning with several pre-trained CNN models in detecting brain tumors.

Table 5. Research list of using transfer learning with different pre-trained CNN models

Year	Source [Ref.]	CNN model	Accuracy
2018	[72]	AlexNet, and GoogLeNet	92.7% and 94.5%
2019	[73]	GoogLeNet	98%
2020	[61]	DebseNet201 and Inception-v3	99.51% and 99.34%
2020	[74]	AlexNet, VGG16, VGG19, ResNet18, and ResNet50	> 95%
2020	[58]	VGG16, ResNet50, and Inception-v3	90%, 95%, and 55%
2021	[36]	InceptionResNet-v2, and Inception-v3	93.1% and 91.24%
2021	[17]	AlexNet, VGG16, GoogLeNet, ResNet50, and Inception-v3	Up to 100%
2021	[11]	VGG16, VGG19, and ResNet50 with classifiers: Softmax, SVM-RBF, and SVM-Cubic	VGG19+SVM-RBF: 96%

3. LIMITATIONS (CHALLENGES) AND ALTERNATIVE SOLUTIONS

In detecting brain tumors using DL, various difficulties are frequently considered. Limited datasets, overfitting, and vanishing gradient are DL models' most important challenges. Such difficulties are described in the following, with possible alternatives being consequently offered.

3.1. Limited datasets

One of the main characteristics of DL is a highly data-hungry consideration [75]. Achieving a well-behaved performance model required extensive data (see Figure 2 [56]). Investigating the available datasets showed that some seem sufficient to obtain a good performance model. In particular, most cases show a shortage of data to use directly. However, three suggested techniques are available to address this difficulty properly. Employing transfer learning after collecting data from similar tasks is the first choice. Note that the actual dataset is not augmented with TL, but it can help improve the actual input data representation and mapping function [76]. The second choice includes using a well-trained model from a similar task and fine-tuning the last one or two layers according to the dataset [69]. The last suggested choice is to use simulated data for enlarging the dataset. Some cases may require creating a simulator. The result involves collecting much-simulated data as required [77].

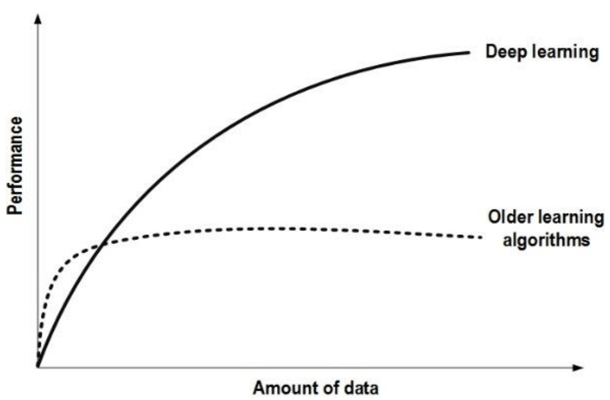

Figure 2. Relationship between the amount of data and the DL performance [56]

3.2. Overfitting

In general, all DL models produce many parameters correlating in a complicated way. These parameters can cause data overfitting during the training stage and reduce the model's potential to obtain a superior performance at the testing stage [78]. This issue should be considered completely and correctly when proposing the DL approach. Although recent studies released that the implied bias of the training stage supports the model to overwhelm critical overfitting [79], developing techniques to solve the overfitting problem is still necessary. Conversely, three groups of DL algorithms are available to overcome this problem. The first group includes the most widely used approaches like dropout, batch normalization, and weight decay and works on model parameters and architecture. Among these approaches, weight decay as a universal regularizer is highly used in approximately all machine learning algorithms. The second group includes data augmentation and corruption and acts on the model inputs to make the learned distribution not mirror the original one. The last group acts as the model output. Pereyra *et al.* [80] proposed a method to penalize the over-confident outputs for regularizing the model. They also released that this method could potentially regularize both CNN and RNN models.

3.3. Vanishing gradient

Working with ANN models that use gradient-based learning and backpropagation techniques raises a vanishing gradient problem, mainly in the training stage [81]. In particular, all models' weights are updated relatively proportional to the partial derivatives of the error function and based on the current weight in each training iteration. Vanishing a small gradient may cause weight updating failure in some cases. Moreover, the worst-case includes stopping the model completely after the training process cannot continue. The sigmoid function may shrink a sizeable input space into a very small one, similar to other activation functions. The derivative becomes small because the sigmoid function has a small variation at the output owing to the large variation at the input. These activation layers are used only in some layers of the shallow network, which are not an important issue. In contrast, the gradient becomes small during the training stage using more layers; hence the network acts perfectly. However, to obtain the gradients of a neural network, the backpropagation technique is utilized. Firstly, obtaining the network derivatives in a backward direction (i.e., get going from the last layer (source) and ending at the first layer (destination)). Then, multiplying these derivatives together is also in a reverse direction. Thus, as the gradient propagates backward to the first layer, it will decline exponentially. In other words, since the gradient is small, the weights and biases of the first layers will not be updated effectively through the training stage. Additionally, the overall network accuracy will decrease in such situations since the first layers are often crucial in distinguishing the fundamental elements of the input data. Conversely, the solution is in using activation functions, as they do not have the squishing property. The ReLU is the familiar choice because it does not produce a small derivative [82]. Adding batch normalization is another solution [83].

4. CONCLUSION

This paper is a comprehensive article suitable as a starting point for researchers to demonstrate essential aspects of using deep learning in diagnosing brain tumors. It is restricted to detecting brain tumors (binary classification) using MRI datasets between 2020 and 2021. Early research is not included since several papers covering the subject are available. In contrast, most research during 2021 is focused on segmentation and multi-classification. Accurate detection is a critical stage to open the gate for multi-classifications. Dataset plays a significant role in diagnosing brain tumors. Various datasets are available online but often have a limited number of images. Thus, data augmentation and transfer learning are alternative solutions where researchers widely investigate these concepts. The research includes other concepts by presenting different CNN architectures (standard or designed). Moreover, the most limitations in applying the deep learning approach, including overfitting, and vanishing gradient issues, are also discussed with their solutions.

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