Application of Deep Learning in Healthcare: A Survey on Brain Tumor Detection

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Abstract. Brain tumors are one of the most dangerous diseases that continue to be threatened worldwide.As a result, the diagnosis and treatment in the early stages are very important in this case. As a result, the diagnosis and treatment in the early stages are very important in this case. Furthermore, the determination of the correct nature of the tumor is a sensitive process in patient treatment .In recent years, with the advancement of deep learning solutions in computer vision, such as image segmentation, image classification, and object detection, promising results have been achieved in the accuracy of medical diagnosis.In this paper, we propose the most famous deep learning model and architecture used to predict the existence of brain tumors from an MR image dataset.

Keywords—Deep learning, Segmentation, Classification, CNN.

1 Introduction

Artificial intelligence is a new computer technology used to research and develop theories, methods, techniques, and application systems. This advanced technology can impact all aspects of human life[40–41]. The health care system has benefited from the advanced development of medical artificial intelligence. This technology plays an important role in the decision-making of clinicians in the formulation of a diagnosis, the making of therapeutic decisions, and the prediction of treatment results [36, 37, 38, 39].

The International Agency for Research on Cancer reported 18,264 cases (for both sexes and all ages) with a [14,370-23,213] uncertainty interval in 2020 [3], in Morocco, 1607 new cases and 1347 deaths in the period (2006-2015) with a 3823 prevalence in these years[52]. Brain tumors are masses of cells that grow uncontrollably in the brain.There are a variety of types of brain tumors, including non-cancerous (benign) and cancerous (malignant) tumors.

Malignant tumors can be primary brain tumors if they originate in the brain or secondary brain tumors if they migrate from other parts of the body.
In this survey, we reviewed studies on brain tumor detection with a focus on new technical aspects of deep learning, such as models and architectures used in MR image segmentation and classification algorithms.We also provide insightful discussion about the different techniques used. Before discussing the results of each one of these methods, we will start in Section 1 with a short introduction to the different applications of deep learning for a brain tumor. Then, in Section 2, we review the fundamentals of learning-based systems.There is a tumor detection method comparison in section 3.Next, in Section 4, We explain some future development direction and open challenges in the detection of brain tumors. Then we finish in Section 5 with a conclusion.

1.1 Fundamental concepts

In this first section, we explore the fundamental process of tumor detection. The process begins with MR image preprocessing and data analysis. Then, segmentation is a very important step in medical images that can help identify the brain tumor regions. Next, we passed to the extraction of features and classification of the nature of tumors.From the input of MR images to the detection of tumors, AI solutions are present at every stage, utilizing deep learning neural networks and machine learning models Fig1.

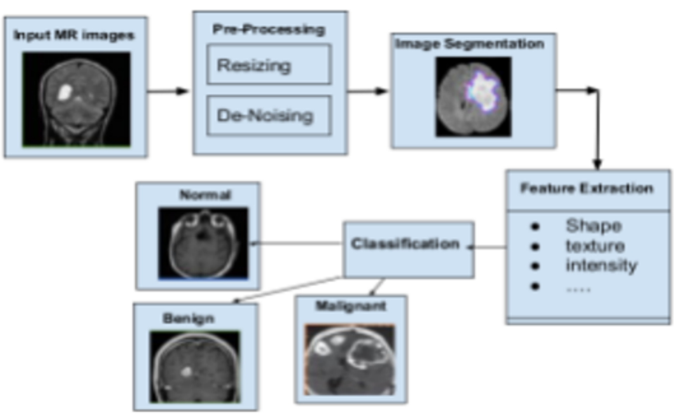


Fig. 1. The process of brain tumor detection.

1.2 MR images

Magnetic resonance imaging (MRI) is one famous imaging modality in radiology used in diagnosis, treatment, and surgery planning, aiming to provide all the information needed for the right treatment plan.[1]. MRI techniques generate a high-resolution image,while we can distinguish contrasts , are also sensitive to specific tissues or fluid regions. without the need for invasive procedures or injection contrast. It is the most suitable for the metabolic or biophysical properties of brain tumors [6].
Furthermore, the World Health Organization (WHO) classifies brain tumors into four categories (Grade I–IV). Tumors start from a low grade and gradually move to a higher grade. In other words, it starts as benign and with time it becomes malignant.

The most frequently MRI sequences used are (I) T1-weighted images, (II) contrast-enhanced T1-weighted images (T1c), (II) T2-weighted images, and (IV) Fluid Attenuation Inversion Recovery (FLAIR) images. Information from various sequences can be used to analyze the various subregions of brain tumors.As illustrated in Fig. 2, they use multiple MRI slices to view different tumor regions.The standard approaches for detecting and analyzing brain tumors are magnetic resonance imaging (MRI) and computer tomography (CT) [2]. Low-grade gliomas (LGGs), which are benign and grow slowly, are categorized as grades I and II.High-grade gliomas (HGGs) at grades III and IV are malignant and aggressive. [1]depending on their malignancy or benignity.

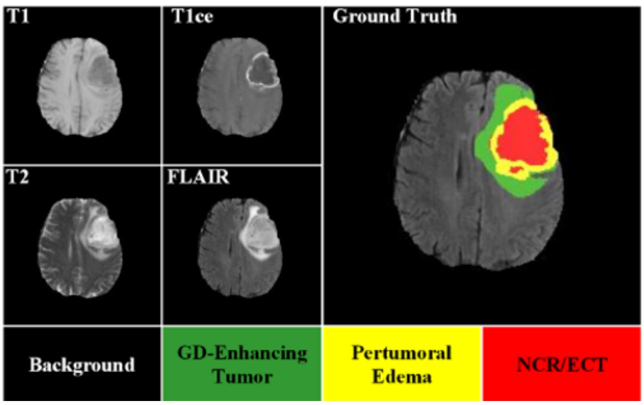


Fig. 2. Brain segmentation map with different modalities

The challenges related to the segmentation of brain tumors and their detection are :
- Morphological uncertainty: Different brain tumors vary with a great deal of uncertainty, tumor subregions may also be varied in size and shape.
- Location uncertainty: Glioma tumor is caused by a mutation in the gluey cells that surround nervous cells. Because of the large spatial distribution of gluey cells, an HGG or LGG glioma can occur anywhere in the brain.
- Low contrast: with low contrast, the image can be blurry and hard to detect.
- Annotation bias: some annotations connect all the small regions together.

1.3 Available datasets of MR images

In this table, we cite the famous available dataset of brain tumors used for segmentation and classification with MRI images.

Table 1. Available dataset of brain tumors

Ref	Database	Description	Features
[6-7]	BRATS	Brain tumors Segmentation challenge	Evaluation of novel methods of brain tumors segmentation.
[10]	OASIS	Open Access Series of Image Studies	Development of Neuro-anatomical atlases, and development of segmentation algorithms.

[26]	HRS	The High Resolution Fundus	Evaluation of reconstruction algorithms and development of segmentation algorithms.
[10-11]	TCIA	The cancer Imaging Archive	Prediction of head and neck cancer.
[16-17-18]	IBSR	The Internet Brain Segmentation Repository.	Evaluation and expansion of segmentation methods.
[19-20]	Brain web	Stimulator of Brain Database.	3D MRI Reconstruction based on CNN and reduction of noise.
[21]	NBIA	National Biomedical Imaging Archive	Quantitative Imaging Network.
[14-15]	The Whole Brain Atlas	Harvard Whole Brain Atlas	Features Extraction from brain images by CNN.
[12-13]	ISLES	Ischemic Stroke Lesion Segmentation.	Stroke lesion segmentation.

1.4 Preprocessing of MRI Data

The preprocessing of an MR image dataset is one of the most important steps in the detection of tumors. The dataset uses different research; it has a different shape (width x height) and depth, and also, MR images may be corrupted with different noises, so it is required to resize the input images then remove the noise.

1.5 Feature Extraction

Feature extraction provides a complete characterization of the tumor. In this step we extract higher level information such as shape (area, perimeter, circularity, etc.), texture (correlation, contrast, cluster, etc.), and intensity (main, variance, etc.).

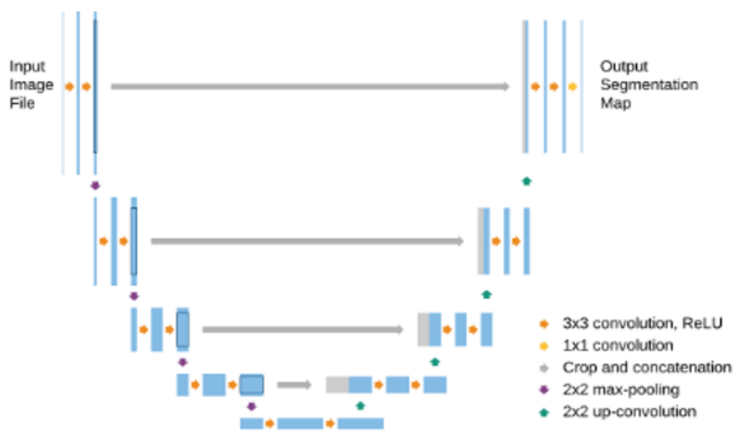
1.6 Deep learning approaches

Deep learning techniques based on fundamental machine learning: unsupervised, semi-supervised, and supervised learning. Furthermore, deep reinforcement learning (DRL).The most famous types of deep learning networks are convolutional neural networks (CNNs), recursive neural networks (RvNNs), and recurrent neural networks (RNNs). CNN is the most used in medical imaging applications among the other networks. even in segmentation, classification, or detection.

1.7 Segmentation

Image segmentation plays a crucial role in detection of glioma tumors. That is why we need to quantify the outcome of image segmentation from one or multiple image modalities (Fig 1). Methods based on deep learning have been reported with promising outcomes. In

this section, we presented two main designs for brain tumor segmentation using deep learning: efficient module design and network architecture design.
For designing effective modules, there are two principal models: the first one is based on learning high-level semantic localization specified by expanding the previous field, feature fusion updates, and other forms. The second approach is to reduce the number of network parameters and accelerate the training by reducing the time. The design of the network architecture used for segmentation is divided into architecture with single or multiple path networks and architecture with encoder and decoder networks. Networks with simple and multiple paths are used to extract features and classify the center pixels of the input patch. In the case of encoder-decoder networks, the encoder extracts a deep feature from a part or the whole image, then the decoder matches it with the segmentation.
Researchers have started to focus on solving a variety of deep neural networks problems. Zikic and al [43], Havaei et al. [44], and Pereira et al. [45]. Aims to develop a deep convolutional neural network (DCNN) to obtain precise segmentation of brain tumors. With progress made by Fully Convolutional Networks (FCN) [46] and U-Net [47]. In order to achieve end-to-end tumor segmentation, the most recent advancement in fully convolutional networks focuses on the construction of fully convolutional encoder-decoder networks without fully connected layers.
U-Net architecture, developed by Ronneberger et al., in 2015. This architecture consists of two paths. The first path is an encoder, also called an analysis path.The second path is the decoder, composed of up-convolutions and concatenations with features from the contracting path [42].



. Fig. 3. Basic U-net architecture. [42]

2222222Researchers have developed a multiple architecture based on U-Net networks as flowese : 3D U-NET, RESIDUAL U-NET, RECURRENT U-NET, DENSE U-NET, U-NET++, ADVERSARIAL U-NET, ENSEMBLE U-NET.

1.8 Classification

Classifying brain tumors is the last step in detecting the type of tumor. It is a sensitive stage while we identify exactly the type of tissue (normal,benign, or malign tumor). Most conventional methods used for classification, as following Support Vector Machine (SVM),

Artificial Neural Networks (ANN), and Naive Bayes (NB), were only capable of detecting brain tumors in a very small percentage of cases in the early stages, which frequently resulted in a person's death. [4]
The recent architecture used for image classification is Capsule Neural Network. (Caps Net) built on capsules, each one is a group of neurons representing one instance of a visual entity. Two types of capsule networks have been suggested: supervised learning (Sabour et al.[53], 2017; Hinton et al.[54], 2018) and unsupervised learning (Kosioreket al.[55] ,2019). J.S.T. Purni and authors [4] provided a Capsule Neural Network (Caps Net) model to avoid increased mortality in patients with brain tumors, and reduce the time to accurate diagnosis. Caps Net is a type of artificial neural network.

2 Comparaison

There are several deep learning models developed for segmentation, and classification. In this section, we briefly compare some of the most popular architecture of segmentation with Dice score parameter Table 2. And for classification we use the accuracy result to compare models and algorithms used for classification in several researches Table3 .
Dice Score: A variable for evaluating the overlap rate of prediction results and ground truth. Dice varies from 0 to 1, the best prediction result is a value close to 1.

Table 2. Comparison of Dice score in recent works for brain tumor segmentation.

Reference	Year	Data	Dice score			Technique used
			TC	*ET*	*WT*	
Xiangyu Li ,al.[24]	2019	BraTS 2019	0.813	0.771	0.886	Multi-step Cascaded Networks
M.Pendse,al [30]	2021	BraTS 2020	0.92	0.88	0.93	Partial Depth wise Separable Convolutions
Shujing Li and Linguo Li [25]	2022	BraTS 2018 and BraTS 2019	0.800 ± 0.01	not determ-ined	0.819 ± 0.011	DRT-Unet: Dilated Convolution-Dense Block-Transformation Convolution-Unet
Ahmed M. Gab Allah and al [22]	2023	Created by Cheng et al. (2015)	0.888	0.9176	0.876	Edge U-Net model with boundary information
R.Raza, al.[23]	2023	BraTS 2020	0.835	0.80	0.86	deep residual U-Net

The final step of detection is the classification of the brain tumor to identify the type of the tumor. In this table 3 we compared some classification techniques used by researchers with the accuracy result calculated with (1) .

Accuracy =(TP +TN) / (TP+FP+TN+FN) (1)

Where :
FP and TP : false and true positive rates
FN and TN: false and true negative rates.

Table 3. Comparison Accuracy in recent works for brain tumor Classification .

Ref	Accuracy	Data	Algo classification
[31]	From 91.51% to 94.233	provided by Cheng [32]	RELM (Regularized Extreme Learning Machine)
[33]	From 88.44% and 86.87%	Privet dataset (354 MRI)	Caps Net (Capsule Neural Networks)
[34]	99.02 % and 98.69 %	Public dataset from Kaggle	IACO (improves the and colony optimization) ResNet algorithm

3 Future trends and challenges

With all of this advanced deep learning model and architecture used in prediction, there are some challenges: first and foremost, the diversity of tumors in shape and intensity; a balance between the number of imaging studies and clinical features; the time commitment; the need for second opinions from health professionals; and, finally, the problem of patient privacy.

When using Deep Learning, several issues are taken into consideration . The most difficult ones are listed below and also several possible alternatives are provided accordingly.

3.1 Availability of Database

Many researchers have a passion for this area, but the number of publicly accessible databases remains very limited. This limits the experimentation and testing of new methodologies. As you know, The main requirement of any in-depth learning model is an enormous amount of annotated data to achieve higher accuracy scores.

3.2 End-to-End Deep Learning

End-to-end models can recognize a tumor in an input MR image, segment it, classify it, and categorize its type as a result.

3.3 Merging Fog and Cloud Computing

The computer fog facilitates the regular processing and generates the output quite quickly using the capacities of the on-board network. IIn the realm of medicine, data collected from a specific MR capture device should be rapidly formulated and processed over various layers of cloud and fog for effective analysis. [49]

3.4 Advanced Data-Enrichment

The augmentation of Dataset can be utilized to generate data to some extent. Dataset can be augmented to generate data to some extent. The quality of the generated data decreases after a certain amount of enhancement. Therefore, more improved techniques of data-enrichment should be investigated. Among advanced data enrichment are Generative Adversarial Networks (GANs) which are widely used for many applications in a variety of fields, such as medical image synthesis [50], compression detection MRI [51], and super resolution [52].

3.5 Confidence and Explainability

Considering the usability of methods by physicians is another critical aspect that should be taken into account in the development of new learning methods.

3.6 Internet of Things for the medical field

The Internet of Medical Things (IoMT) has become a magnet for increased researcher focus due to rapid development of smart technologies and real-time data sharing by using the Internet of Things (IoT) [48].

4 Conclusion

The role of science is to save humanity from diseases like brain tumors, with recent advances in medical imaging technology inspired by deep learning methods such as models or artificial neural networks . These methods were effective at detecting tumors. The goal of this paper is to present some novel architectures for segmenting and classifying brain tumors using multi-modal MRI images that can aid researchers in their experiences.

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