Review and Evaluation of existing deep learning methods for Brain Tumor Detection

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Abstract: When it comes to medical image processing, segmenting brain tumors is an essential task. Patients' chances of survival are increased and treatment options are improved when brain tumors are detected early. It requires a great deal of time and work to manually separate brain tumors from the many MRI pictures obtained during clinical routines in order to diagnose malignancy. Automatic brain tumor segmentation of images is required. This study summarizes methods for segmenting brain tumors using magnetic resonance imaging (MRI). Automatic segmentation using deep learning approaches has been increasingly popular as of late.
Since they are more efficient and offer cutting-edge outcomes than previous approaches at solving this issue. Using deep learning techniques, the enormous amounts of MRI-based image data can also be analyzed efficiently and objectively. There are a plethora of review articles out there that focus on the tried-and-true methods of segmenting brain tumor images from MRI scans. In contrast to previous research, this study zeroes in on how deep learning techniques have evolved in this area. First, the basics of brain tumors and how they are classified are given. Subsequently, the latest algorithms are examined, emphasizing the emerging field of deep learning techniques. Lastly, a review of the situation is given, along with plans for standardizing MRI-based techniques for brain tumor segmentation into regular clinical practice.

Keywords: Transformers, Medical Image Analysis, Deep Learning, Brain Tumor, Magnetic Resonance Imaging, BraTS, Machine Learning

I.INTRODUCTION

A. *About Brain Tumor*

Deep Learning (DL) techniques enable computer models with several processing layers representing data in various scenarios of abstraction. Deep learning techniques are currently widely applied in nearly every field, with bioinformatics—the processing and analysis of medical images—using them most frequently. Because of deep (machine) learning, our understanding of pathology, brain tumors, lung, cancer, breadbasket, heart, and retina has significantly improved and changed. This composition aims to assess the major deep knowledge generalities (such segmentation, type, prophecy, and assessment) that are pertinent to brain excrescence analysis while considering the wide range of deep knowledge operations. This document represents a review that was finished by assembling multiple scientific works on the subject. Along with a convincing taxonomy of the discourse terrain derived from the literature, the essential elements of this developing field have been put forth and examined. There is a section for critical discussion at the end that lists the drawbacks of deep learning techniques and makes recommendations for possible future research paths in this crucial field.

The term "tumor" describes an aberrant development in the brain. Tumors can evolve into cancer, a dangerous disease that causes 13% of all deaths globally. Globally, the prevalence of cancer is rising at an alarming rate. Early diagnosis of cancerous tumors is crucial. Accurate tumor diagnosis in medical imaging requires a high degree of radiologists' competence and knowledge. Medical imaging techniques and approaches, including computed tomography (CT), magnetic resonance imaging (MRI), ultrasound, and X-ray, have a substantial impact on patient therapy and diagnosis [1].

Brain tumors can be classified into two primary categories: benign (non-cancerous) and malignant (cancerous). The World Health Organization (WHO) has further classified malignant tumors into categories I through IV [4]. The classifications of astrocytomas include Low-Grade Astrocytoma (Grade II), Anaplastic Astrocytoma (Grade III), and Glioblastoma (Grade IV). Tumors classified as Grade-I and Grade-II are considered to be less aggressive types of semi-malignant tumors. Malignant tumors of Grades III and IV have a major influence on the patient's health and can potentially be fatal.

Numerous image processing methods and techniques have been utilized in the identification and cure of cerebral neoplasms. Segmentation functions as the foundational phase of image processing methods, utilized to separate the affected brain tissue from magnetic resonance imaging (MRI) [3]. The tumor region requires segmentation to facilitate diagnosis, treatment, and assessment of cancer therapy efficacy. A range of partially automatic and fully automatic segmentation techniques are utilized to delineate tumors [4]. Brain tumors can be segmented utilizing various MRI techniques and sequences, including T1-weighted (TI), T1-weighted contrast-enhanced (T1c), T2-weighted, and T2-weighted Fluid Attenuated Inversion Recovery (FLAIR) methods.

Researchers conducting tumor segmentation studies frequently employ machine learning methods for pattern classification, including Hyperplane Classifiers (SVMs) [6-8] and Random Decision Forest (RF) [5]. Brain tumor segmentation studies are increasingly using deep learning-based approaches and methodologies because of their superior performance within the realm of picture analysis disciplines like object identification [9], image classification [10], and semantic segmentation [11–13].

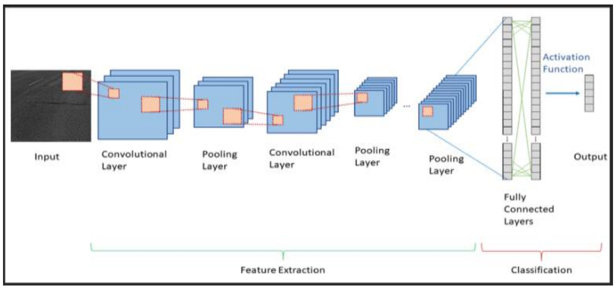
A substantial amount of studies articles, the majority of those are not long ago, are included in the evaluation in order to establish the majority of pertinent contribution of deep learning to brain tumor identification. These papers offer a range of deep learning techniques for studying brain tumors. The aim of this review are threefold: (a) to illustrate the beneficial effects of deep learning on brain cancer research as a whole; (b) to draw attention to research questions regarding effectively applying deep learning techniques to brain tumor activities; and (c) to emphasize the substantial role that artificial intelligence (deep learning) has played in the analysis of brain tumors.

B. Background

The standard method for visualizing brain tumors in clinical practice is magnetic resonance imaging, offering structural, microstructural, functional, and metabolic data [57]. Furthermore, cutting-edge enhanced imaging methods are always being created to enhance brain tumor detection, characterisation, and response evaluation [56]. Consequently, MRI has laid the groundwork for a plethora of AI applications in the field of brain cancer imaging. For more information about brain tumors, see [55].

1) Deep Learning

The field of deep learning (DL) draws on techniques developed in neuroscience to improve AI [30]. Segmentation, object recognition, and classification are just a few of the medical image analysis tasks that have recently become critically important for deep machine learning systems. Convnets (CNNs) are the most widely used deep learning technique for developing methods for segmenting and classifying brain tumors [54]. The spatial associations between individual MRI "voxels" might be educated by CNNs. Within convolutional neural networks (CNNs), a number of filters are positioned above an input picture in order to identify various aspects that define the image. Nearly all convolutional neural network (CNN) models consist of the following layers: input, convolution, activation function, pooling, completely connected, output, and pooling. The network's input image is fed into it at the input layer so that the higher layers can process it. By utilizing convolution, pooling, and activation functions, the image's high-level characteristics are extracted [54], while object segmentation, image classification, the fully linked layer is responsible for object recognition and other related tasks. The output layer generates the network's final forecast or results. Shown in Figure 1 is the overall architecture of a ConvNets (CNN).



2) Methods and Materials used for the review

The articles in this review were released between 2019 and 2022. This paper includes a few studies that were published before to 2019. In particular, our focus was on research that developed ML-based approaches for brain tumor classification and segmentation, CNN, DCNN, GoogleNet, VGGNet, ResNet18, ResNet34, Alex-net, and other similar tools. The relevant papers were located by searches in the scientific literature databases ScienceDirect, Google Scholar, and PubMed. Furthermore, we conducted a search for journal articles utilizing the MDPI, or Multidisciplinary Digital Publishing Institute's online database. We performed searches utilizing the terms: DL, classification, segmentation, and brain tumor. Furthermore, a collection of terms concerning deep learning's segmentation and classification functions brain tumors, including transformers, convolutional neural networks, deep convnets, and traditional machine learning, was amalgamated with the aforementioned search terms.

3) Datasets

Over the years, MICCAI, or the Medical Image Computing and Computer Assisted Intervention Society has supported a number of initiatives and open challenges to encourage the creation of digital health tools and medical equipment for computer-assisted diagnosis. The majority of research employed the MICCAI Society's datasets to assess the effectiveness of their methods. The additional datasets' names are also displayed below. Since most benchmark datasets are tiny, developing DL models from start to finish can be difficult.

Table 1. Available Datasets

BraTS 2012	**BraTS 2013**	**BraTS 2014**	**BraTS 2015**
BraTS 2016	BraTS 2017	BraTS 2018	BraTS 2019
BraTS 2020	BraTS 2021	TCIA	Radiopedia
CE-MRI dataset	Brain MRI Images	Br35H dataset	MSD dataset

Figure1. Convolutional Neural Network Architecture

Commonly used Datasets [58]

II. LITRATURE SURVEY

According to recent research publications, deep learning approaches and algorithms have demonstrated strong performance in supervised machine learning and image categorization. Gliomas, meningiomas, and pituitary tumors are a few of the different kinds of brain tumors. Malignant brain tumors are sub classified as high-grade III and IV, while benign brain tumors are classified as low-grade I and II. The most recent studies on brain tumor analysis are fully explained in the following sentences. The different data sources and how they were acquired are shown below.

In 2023, **K. V. Archana** et. al. [29] used KNN and achieved 96.9% accuracy rate was 96.9%. They found the accuracy improvement to 97.7% using K-Nearest Neighbor Bagging Ensemble (BKNN), a novel technique for diagnosing brain tumor illness, employs predictive logic.

In 2023, **Peddamallu Gangadhara Reddy** et. al. [28] employed K-means to investigate the kernel Fuzzy c-means (KFCM) approach to segment Self-Organising maps (SOM). Later, the SOM is merged with KFCM to get findings that are less time-consuming and more accurate than those from previous approaches. Skewed data enhanced the performance of networks with more SOMs. The suggested strategy beats the most recent and cutting-edge algorithms like k-means in terms of sensitivity and accuracy, according to the tests.

In 2022, **Sekhar, A.** et. al. [26] created deep characteristic-based classification models for cerebral tumors. Deep features are those features that are eliminated from CNN models. A pre-trained ConvNets (CNN), extraction of features using GoogleNet, Softmax as the activation function, Hyperplane Classifiers (SVM), and Nearest Neighbor Classifier (K-NN) classifiers were all part of the transfer learning technique that went into developing its suggested mode. The suggested model achieved an accuracy rate of 95.82% when tested with datasets from CE-MRI Figshare and the Harvard medical repository. The convolutional and fully connected layers of pre-trained models are common places to find these features.

In 2021, **Kang, J.** et. al. [27] focused on the identification of cerebral neoplasms, utilizing ensemble characteristics to improve the accuracy of results, particularly for datasets of significant size. The procedure of feature extraction utilized 13 already trained deep ConvNets (DCNNs), from which the top 3 features were chosen for subsequent processing. A total of nine machine learning classifiers were evaluated, and the Hyperplane Classifiers (SVM) with the Gaussian kernel demonstrated superior performance compared to the other classifiers. The study utilized datasets known as BT-small-2c, BT-large-2c, and BT-large-4c, each representing different sizes and complexities. The accuracy achieved was an astounding 98.50%.

In 2021, **Deepak, S.** et.al. [25] created an automated tumor characterization method which was essential in CAD systems used to diagnose neurological disorders. They faced challenges in tumour categorization using MRI images seen in the brain because of the limited number of medical imaging databases. In order to tackle this issue, suggested method incorporates a blend of ConvNets (CNN) features alongside Hyperplane Classifiers (SVM). The system, which operates without human intervention, obtained an accuracy rate of 95.82% in classifying data, surpassing the most advanced method currently available. The CNN-SVM technique entails less computations and memory demands in comparison to classification based on transfer learning.

In 2021, **Jena, B.** et. al. [24] focused on the classification and segmentation of brain tumors utilizing machine learning and image processing methodologies. Seven techniques for generating texture features were utilized, including Mrgin Classifiers (SVMs), Nearest Neighbor Classifier (KNNs), Gradient Boosted Trees (BDTs), Bagged Decision Trees (RF), and Ensemble Learning Techniques. The results indicated classification accuracies of 94.25%, 87.88%, 89.57%, 96.99%, and 97% for FLAIR-, T1C-, and T2-weighted MRIs, respectively. Additionally, a mean Dice Similarity Coefficient (DSC) of 90.16% was achieved for hybrid segmentation.

In 2021, **Ahmed, B.** et. al [23] used deep CNN as key method. Finding a solution was the primary goal of the research employing a deep ConvNets (CNN) to diagnose brain cancers by analyzing MRI data. The study utilized a dataset of 1258 MRI scans obtained from 60 patients, encompassing three separate brain tumor types and a comparison group of individuals with healthy brains. A deep ConvNets (CNN) methodology was utilized for feature extraction, with 96% precision. The delicate nature of the method heightened as the number of epochs increased, while the error rate diminished with the number of epochs. The system underwent testing on 25 novel MRI pictures for each category, attaining precision rate of 96%. The study revealed that deep convolutional neural networks (CNN) are a highly effective approach for learning, extracting, and classifying features from MRI images.

In 2020, **Jiang, Y.** et. al. [21] in a dynamic contrast material-enhanced (DCE) breast MRI trial testing radiologists' ability to distinguish noncancerous from cancerous lesions, an AI system increased the average AUC from 0.71 to 0.76. Of the 111 breast MRIs studied, 54 showed malignant tumors and 57 showed noncancerous ones. Using BI-RADS category 3 as the criterion improved mean sensitivity, whereas category 4a did not. There was no difference in average specificity between BI-RADS categories 4a and 3. The study found that AI improves radiologists' ability to distinguish benign and malignant MRI breast lesions.

In 2020, **Saba, T.** et.al. [19] provided a blend of human-crafted and deep learning features for image segmentation. The study used the Grab-cut method to enhance the precision of feature extraction by utilizing the VGG-19 CNN model and incorporating hand-crafted attributes including form and surface quality. The datasets utilized consist of MICCAI and BRATS from the years 2015, 2016, and 2017, achieving a remarkable accuracy rate of 99%.

In 2019, **Mamta Mittal** et al. [3] an approach to image segmentation of brain tumors was introduced, utilizing a combination of Stationary Wavelet Transform (SWT) and Growing Convolutional Neural Network (GCNN), grounded in deep learning methodology. The aim is to enhance the precision of conventional systems. The proposed technique exhibits superior performance regarding accuracy, Quadratic Loss, peak SNR, and other performance metrics when contrasted with Hyperplane Classifiers (SVM) and ConvNets (CNN) in a comparative analysis.

In 2019, **Aparna Natarajan** et. al. [14] developed a system for brain tumor segmentation in MR pictures employing fuzzy logic and a spiking neuron model (FL-SNM). The procedure involves pre-processing phases such as MKF, ADF, FLDA, and FL-SNM, achieving an accuracy rate of 94.87%.

III. STATE OF THE ART

In the course of research activities researchers have to go through various datasets, techniques, analysis etc. In this section we will be discussing about these aspects of research and state of art regarding investigation into machine (deep) learning for brain tumor identification. Numerous strategies have been put forth by researchers to build these data sources and, consequently, the ability of methods for detecting tumors. The most widely used method in neurology for obtaining precise images of the brain and other cranial structures are magnetic resonance imaging (MRI) scanning. For training and testing, a variety of datasets are available, including BRATS, OASIS, TCIA, IBSR, BrainWeb, NBIA, and The Whole Brain Atlas.

In the field of brain tumor identification, many studies employ a variety of methodologies, but it has been found that combining several strategies to accomplish a goal produces superior results. In comparison to using only one approach, hybrid methods combine two or more approaches. Table 3 provides some examples of how to use these strategies to the study of MR images.

Table 3 Hybrid techniques in analyzing MR images

Technique	Target	Result	Ref.
This category includes supervised learning approaches, genetic algorithms, and wavelet transforms.	MRI image classification of different brain tissues	This procedure is accurate, simple, non-invasive, and affordable.	[32]
Sobel edge detection, morphological procedures, and K-means.	Brain lesions in MRI and CT scan pictures can be distinguished.	Compared to manual demarcation, it achieves a high accuracy of about 94%.	[33]
Margin Classifiers and Fuzzy C-Means Clustering.	MRI images can detect brain tumors.	Give a bracket of brain MRI pictures an accurate and more effective outcome in the shortest possible time.	[34,35]
K-Means, SVM, and Nonsubsampled Contourlet Transform.	Brain tumor classification using MRI images.	Greater classification accuracy.	[36]
Feature extraction method (PCA), Berkeley Wavelet decomposition (BWT), Grey Level texture Matrix (GLCM), as well as the KSVM kernel support vector machine.	Classifying MRI images and detection.	The suggested technique can be used for screening in the clinic before being accurately and successfully diagnosed by radiologists.	[37]
ANN, Gabor feature xtraction, and fuzzy clustering.	Identification and categorization of brain cancers	The radiologist uses the classifier's output to guide their decisions, and they were able to obtain a classification accuracy of 92.5%.	[38]

There are several methods which come under CNN techniques itself. Below is the list of some most commonly used methods these days in research. Table 4 provides some examples of how to use these strategies to the study of MR images.

Table 4 CNN techniques in the medical field

Ref.	Features	Methods	Testing Sample	Achievement	Accuracy

[42]	Tumor kind, size, form, and features	The DCNN and GoogleNet	thyroid tumors	Enhancing and improving the performance of the image samples.	98.29%
[43]	type of image lesion	Both patch-based and VGGNet DCNN	Prostate cancer	improved forecasting	95%
[44]	Type and size	Inception, ResNet18, ResNet34, and ResNet52-ResNet	Pancreatic cancer	The proposed weighted loss function technique, together with ResNet18, yields the best tumor classification outcomes.	91%
[41]	size, tumor characteristics, and lesion resembling doughnut	VGG-16, U-Net, and FCN	colorectal cancer	Can enhance the existing manual segmentation method, which is inefficient and labor-intensive.	

IV. CHALLENGES

There are some challenges researchers are facing are mentioned in the Table 5 below.

Table 5 Challenges and potential solutions

Challenges	Potential solution(idea)	Example
Classification or segmentation is commonly framed in medical imaging as a binary job that distinguishes between normal and abnormal, or object and backdrop.	By accurately annotating each potential subclass, we turn the multi-class system from the deep learning system [51].	Occasionally, benign categories can be found in normal tissues and categories.
Depending on the medical imaging task being performed, finding images for the odd class may be difficult.	Evaluated data augmentation techniques for lesion segmentation in-depth [50].	During a mammogram, an unsettling lesion is typically not malignant because the majority of cancerous lesions do not result in death.
In a deep learning network, it might be challenging to attain equilibrium between the quantities of clinical data and imaging features.	Connect entire image to the deep network and employ various evaluation methods to direct learning [51].	Typically, medical professionals need to use descriptive data to make an accurate diagnosis.
The variety of tumors and lesions in terms of shape and intensity, as well as the occurrence of different imaging protocols within the same imaging modality, present the most obstacles in CAD.	Traditional machine learning techniques are trained to classify hand-designed features in a thorough, independent process [52].	Simpler machine learning techniques are used to account for bias field effects, non-isotropic resolution, and Rician noise. In MRI, automatic handling is useless.
Deep learning is often considered a "black box" due to the absence of a clear search trail that elucidates its decision-making process.	The feature visualisation is one of the features stated in the feature maps. An element of the input that led to the associated prediction is known as attribution [53].	To precisely define a feature that locates the key areas in an input utilised for prediction, for example, a circle, an edge, or class activation maps (CAMs).

IV. GAPS AND FUTURE SCOPES

With the use of the aforementioned literature evaluation, various research gaps can be filled in order to plan and investigate detection of brain diseases using deep learning.

We identified the research issues according to the current status of this field's research.

- The use of CnvNets (CNNs) to improve MRI image quality is absent [48].
- More accurate model needs to be developed.

Currently, the best accuracy revolves around 98%[42].

- Need of appropriate feature extraction method. Reducing detection time and boosting accuracy can be achieved through the deployment of suitable feature extraction and reduction models [48].
- There is no benchmark dataset supplied for researchers to compare performance of various methods[49]
- Need of hybrid optimization. New hybrid optimization strategy to optimize selected features including texture, size, colour, edge, contrast, and placement is required[46]
- The detection rate is very less. Need serious attention on this gap[50]

V. CONCLUSION

One of the primary objectives in contemporary societies is the prevention of fatal disorders such as brain excrescences. Due to current technological advancements, such as deep literacy, artificial intelligence design concepts have an impact on medical imaging. These techniques allow for precise examination of extremely huge datasets after training models to detect outliers. A number of advanced convolutional neural network (CNN) variations have been suggested for use in image processing, which is similar to the usage of ANNs in picture bracketing and segmentation. One of the many models for machine literacy is ANNs. Processing images begins with segmentation, as it is essential to distinguish between aberrant and sick regions in MRIs. Within the framework of magnetic resonance (MR) imaging, we give an overview of deep literacy styles as well as several other common strategies for bracketing and segmenting brain excrescence. We examined several infrastructures and their uses in medical imaging while concentrating more on CNN. Based on our discussion, we connected the being holes in the sphere and provided a series of future instructions. This article primarily examined the dynamic CNN systems used in medical image processing and their results.

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