A comprehensive study of Brain Tumor Identification using Machine Learning and Deep Learning

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Abstract

The development of a brain tumor is regarded as a severe medical condition that can lead to cancer. One of the most common ways to detect this type of tumor is through the use of nuclear magnetic resonance imaging. This type of imaging scans the brain to visualize the abnormal cells. Machine learning and deep learning are being used in the detection of brain tumors. These methods can help the radiologist make quick decisions and deliver effective treatments. Classification of brain tumors using MRI scans is very important for both the diagnosis and treatment of brain cancer. This process can help speed up the planning and treatment of the patient. It can also improve the survival rate of patients. Developing automatic models of brain tumors is also very beneficial for reducing the human factor. In several studies, these methods were shown to improve the accuracy of brain tumor predictions. In recent years, the development of machine learning and deep learning techniques has been widely acknowledged for their potential to improve the performance of various computer vision tasks, such as image classification and semantic segmentation. Due to the technological advancements that have occurred in the field, a comprehensive survey has been conducted to study the various applications of machine learning and deep learning in brain tumor segmentation.

Keywords: Brain tumor, Machine Learning, Deep Learning, image segmentation

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INTRODUCTION

A brain tumor is a type of abnormal cell that forms in the brain. There are two types of brain tumors: malignant and benign. The former is referred to as primary tumors, which start in the brain, and the latter is secondary tumors, usually found outside the brain. Different brain tumors can cause different symptoms depending on their size and location[1]. For instance, when the tumor is in the part of the brain that's involved, it can cause seizures and headaches. Other symptoms can include difficulty walking and speaking[2]. Although the exact cause of brain tumors is not known, certain factors can increase the risk of developing them. Some of these include exposure to ionizing radiation, vinyl chloride, and Epstein-Barr virus. Studies on the effects of mobile phones have not shown a clear link.

In adults, the most common types of primary brain tumors are meningiomas and astrocytomas. In children, the disease most commonly known is malignant medulloblastoma. Usually, a diagnosis is made through a medical examination that includes a combination of imaging techniques such as C.T. and MRI[3]. The results of a tumor can be confirmed by a biopsy performed after the tumor has been removed. Based on the findings, the tumor can be categorized into different grades. Brain tumor treatment usually involves surgery, chemotherapy, and radiation therapy. Since the tumor is located in the brain, it can return if it's not treated properly. In addition to this, anticonvulsant medication may also be used to decrease the swelling around the tumor.

Some types of brain tumors can grow in a gradual manner and require monitoring. They can also be treated with the use of the patient's immune system. On the other hand, malignant tumors can spread to other parts of the body. Although benign tumors can only grow in one location, they can still be life-threatening. Medical image analysis is a useful tool for medical professionals to improve the quality of healthcare by identifying diseases and investigating clinical issues[4]. It can also help them understand the various factors that affect the development and maintenance of a patient's condition. One of the most challenging tasks in this field is the segmentation of brain tumors. Despite the efforts of researchers, the accuracy of this procedure still remains a major challenge. Due to the complexity of brain tumor segmentation, various factors such as data imbalance, location uncertainty, and morphological uncertainty can be encountered in the process. With the help of deep learning techniques, a number of methods have been developed to perform automatic feature extraction and improve the performance of brain tumor segmentation.

Due to the increasing number of brain tumors being discovered through medical image processing, the field of imaging has been regarded as a new discipline for diagnosing and treating brain cancer. Usually, patients undergo C.T. scans and MRI scans to visualize the tumor. The use of medical imaging techniques such as MRI can help medical professionals identify and treat various diseases. It can also provide them with high-contrast images of the human body. In addition, image analysis is very important for the diagnosis of brain tumors.

Magnetic resonance imaging (MRI) scans are commonly used to visualize the structure of the brain. They feature various statistical features and discrete wavelet transform (DWT) to provide a detailed view of the brain[5,6]. Following the segmentation, detection, and quantitation steps, the analysis process is performed to identify the brain tumor. Due to the complexity of the data collected during the imaging process, the accuracy of the diagnosis of brain tumors is still a major challenge. One of the most common factors affecting this process's performance is the intra-class variability of the data. Hybrid approaches are commonly used to segment and analyze brain tumours from an MRI scan. This procedure aims to provide a detailed view of the brain without the need for surgery[7]. This method can help identify the tumour's exact location and make the detection process easier. Due to the increasing number of cases of brain cancer, the use of MRI scans to determine the size and growth of the tumor has become more popular.

WORK RELATED TO BRAIN TUMOR IDENTIFICATION USING MRI IMAGES

Table 1Major related work

S.No	Author	Algorithm Used	Dataset	Outcome
1.	Mohammad Shahjahan Majib et al. [8]	VGG-SCNet	open-access dataset from kaggle	Precision=99.2%,, recall=99.1%, f1=99.2%
2.	Debendra Kumar Sahoo et al. [9]	Ensemble + Multilayer Perceptron (MLP)	Kaggle brain MRI image	Accuracy=98.08%, F1-score=0.9836, precision=1.0000, sensitivity=0.9677 and specificity=1.0000
3.	Jose Antonio Marmolejo-Saucedo et al.[10]	CNN + Grad-CAM	BRATS dataset	accuracy =97.11%, sensitivity =95.58% and specificity =96.81%
4.	Anil Kumar Budati et al.[11]	KNN + SVM	BRATS 2017 dataset	Accuracy SVM = 98.13% and KNN=92.30%

5.	Emre Dandil et al.[12]	LSTM + Bi-LSTM	MRS dataset	Classification results of Pseudo brain tumor with Glioblastoma=93.44%, Diffuse astrocytoma=85.56%, Metastatic brain tumors=88.33% and Normal brain tissue=99.23%
6.	Asim Zaman et al.[13]	CNN + SVM	BRATS 2020 dataset	Accuracy=93.5%
7.	Wu Deng et al.[14]	CRF + HCNN	BRATS 2013, BRATS 2015	Precision= 96.5% Recall= 97.8%
8.	Md Khairul Islam et al.[15]	Template-based K-means (T.K.) algorithm	BRATS dataset	Accuracy = 95.0%, Sensitivity = 97.36%, Specificity = 100%
9.	Shahzad Ahmad Qureshi et al.[16]	Ultra-Light Deep Learning architecture + SVM	T1-weighted CE-MRI dataset	Average Detection Rate using SVM 99.23% and F-measure of 0.99
10.	Mohsen Ahmadi et al. [17]	FWNNet	Brain Tumor Classification (MRI) dataset from Kaggle	Accuracy = 100%
11.	Ejaz Ul Haq et al.[18]	CNN + SVM-RBF	Figshare dataset	Accuracy = 98.3%
12.	Tejas Shelatkar et al.[19]	YOLOv5	BRATS 2021	Precision= 88%
13.	Khizar Abbas et al.[20]	LIPC	MICCAI	Dice Score of 0.95
14.	Shraddha S. More et al.[21]	CNN	Self-created dataset	Accuracy=87.42%
15.	Heba Mohsen et al.[6]	DNN, SOM-SVM	Harvard dataset	Accuracy=96.97%

DISCOVERY OF BRAIN TUMOR

An intracranial tumor is a type of abnormal tissue mass that can grow and multiply uncontrollably. More than 150 types of brain tumors have been identified. The two main groups of these are primary and metastatic. A primary brain tumor is a type of tumor that's caused by the body's tissues. It can be categorized as non-glial or malignant. These tumors are usually formed in the brain's structures, such as the blood vessels and nerves. Metastatic brain tumors are types of cancer that can arise in different parts of the body, such as the breast or lungs. They usually travel to the brain through the bloodstream. Different types of brain tumors, including cysts, lesions, and tumors, are differentiated depending on their location and the kind of cells they contain. Some benign tumors are harmless, while others are malignant.

Types

A brain tumor is a type of mass or lump of abnormal cells that can be formed on the brain's surface. It can be malignant or non-malignant depending on the type of cells it contains. Brain tumors that are not malignant are not as dangerous as those that are malignant. However, the symptoms of both the conditions are similar, and it is important to perform various tests and screenings in order to determine if the tumor is malignant or non-malignant. A brain tumor can be categorized into two types: primary and metastatic. The former is referred to as a non-glial tumor that starts in the brain. On the other hand, the latter is a malignant tumor that grows in the brain's blood vessels, nerves, and glands. On the other hand, a brain tumor is referred to as a metastasis when the cancer cells spread to other parts of the body. Metastatic tumors are very dangerous and are usually caused by the cancer cells moving from their primary site.

Brain tumors can be further divided into the following:

One type of brain tumor that grows at a slow pace is a chordoma. This type of tumor usually affects people who are in their 50 to 60 years old. It can grow at an abnormal rate and put pressure on the surrounding nerve tissue. This type of tumor accounts for about 0.2 percent of all brain tumors. A type of brain tumor known as a craniopharyngioma is usually difficult to remove. It can be treated through hormone replacement therapy. A type of brain tumor known as a gangliocytomas is rare. It usually affects young adults and teenagers.

A type of brain tumor known as a granuloma is usually benign and can develop under the skull base. It accounts for about 0.6 percent of all brain tumors. The most common type of brain tumor is the meningioma. Most commonly, gliomas are seen in adults. They account for over 78 percent of all brain tumors. The three types of these tumors are oligodendroglial cells, astrocytes, and ependymal cells. Almost half of all spinal cord and brain tumors are astrocytomas. These are usually found in the cerebrum. These are the cells that come from the glial cells. One of the most dangerous types of brain tumors is the glioma multiforme. This type of tumor can grow accelerated and affect people in their 50 to 70 years old. Fig.1 shows the various types of brain tumor.

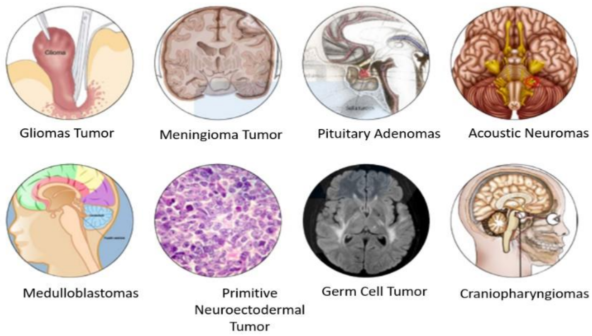

Fig. 1 Various type of Brain Tumor

VARIOUS DATASET AVAILABLE

Currently, most brain tumour detection methods rely on MRI brain image datasets. Due to the increasing number of data sets being collected and analyzed for the detection of brain tumors, the implementation of new projects using big data techniques is being considered. The followings are the few benchmark datasets for MRI image segmentation for detecting brain tumours.

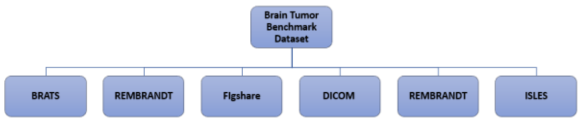

Fig. 2 Major Benchmark dataset

IMAGE SEGMENTATION AND TYPES

The segmentation techniques used in brain tumor MRI are divided into three main categories: traditional segmentation, deep learning-based segmentation, and machine learning-based segmentation. Each category has its own set of algorithms that can be used to perform different tasks.

Detection of tumor using Traditional Method

Threshold-based segmentation

Fig.2 shows that threshold-based segmentation is one of the most common techniques used in brain tumor MRI. A thresholding technique is a type of image segmentation that makes it easier to analyze an image. It converts an image from either a gray or a color to a black and white. It takes into account the pixels within a range that belong to the same category and can be used to divide the tumor into two regions. This method can be used to overcome the issue of uneven gray in the images and improve the contrast and DSC of the scans. The complexity of the segmentation process depends on the size of the threshold. Since the quality of the results depends on the size of the threshold, it is important to select the right one. Unfortunately, the threshold segmentation technique is not very accurate when it comes to identifying complex images. It can only segment simple images.

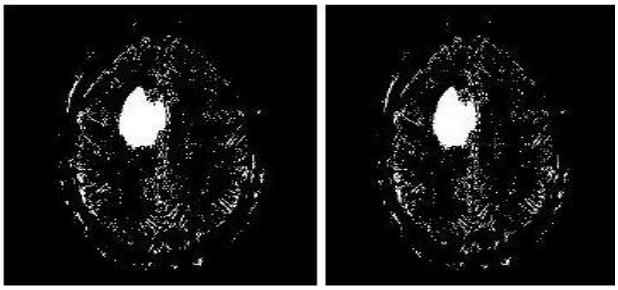

Fig. 3 threshold based segmentation[22]

Region Based Segmentation

The segmentation process recursively adds the neighboring pixels that are connected to the seed pixel. Similarity measures are used to identify regions with varying gray levels. Connectivity is also used to prevent connecting parts of the image. Fig.3 shows region-based segmentation strategy is usually performed by defining a seed pixel. This can be done by randomly selecting all pixels or defining a predefined seed pixel. Follow the top-down approach and divide the image into regions until all pixels belong to the region. The bottom-up approach is to select only the objects that are of interest to the region.

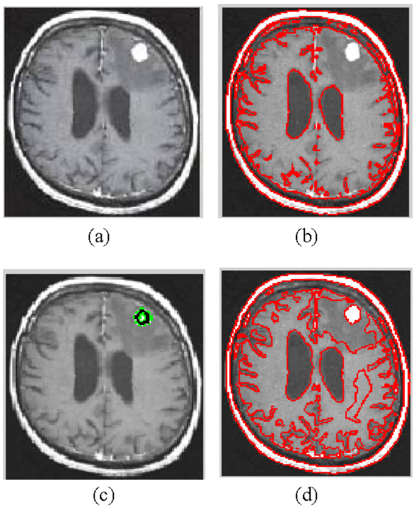

Fig. 4 Region Based segmentation[23]

A similarity measure can be used to identify regions with varying spatial properties and textures in a gray-scale image. It can also be used to compare the intensity difference between the regions and the distance between them. The segmentation strategy is usually performed by merging the regions to separate the single object from the background. There are various techniques that are used in this process, such as the Split and merge algorithm. The advantages of region-based segmentation are that it is faster than traditional segmentation techniques. It can also be performed when the background and object contrast highly. However, it did not produce accurate results when there were no significant differences between the values of the two objects.

Edge Based Segmentation

An edge detection technique is used to find the pixels that are on an object's edge. Various methods are used for this type of detection, such as the Laplace operator, Canny, and Sobel operator. The following two methods can be used to perform edge linking. Local processing involves using gradient and direction to link the edges. Global processing is a bit more complex and involves linking the edges if they have a similar direction vector. This technique is similar to how the human brain processes segmentation. It can perform well in images with good contrast and smooth transitions. However, it does not work well in images with low contrast and smooth transitions.

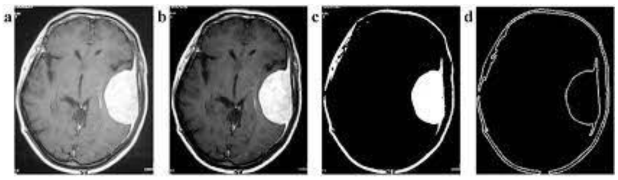

Fig. 5 Edge based Segmentation

Detection of tumor using ML

Machine learning techniques are used to train a classification model for brain tumors shows in fig.5. These methods are usually divided into two levels. The first level is an organizational level, where the classifier decides which features belong to which type of organizational structure. The second level is a pixel level, where the classifier decides which features belong to which category. For example, most traditional machine learning algorithms focus on the K-Nearest Neighbors, SVM, Random Forest, and Dictionary Learning.

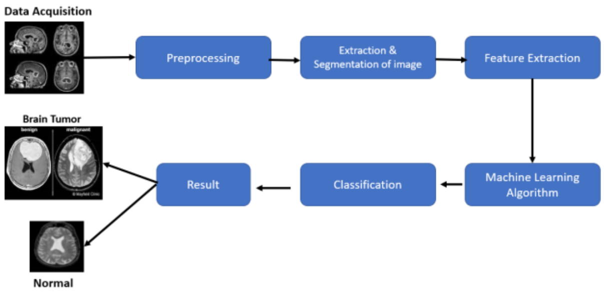

Fig. 6 MRI processing using Machine Learning

Javeria Amin et al.[24] proposed an unsupervised clustering approach is proposed for the segmentation of cancer cells. It utilizes a fused feature vector composed of various features such as the gradient-oriented HOG, the local binary pattern, and the segmentation based on the SFTA. The method is then used to classify the different sub-regions of the tumor. In order to avoid over fitting, a 5-fold and a 0.5 holdout cross-validation method is used. The proposed approach shows promising detection efficiency. G. Manogaran et al.[25] works on medical image database was analyzed and evaluated to validate the accuracy and efficiency of the system. The algorithm's mean error rate was then computed using a statistical model. A machine-learning approach was then used to analyze the over-segments and under-segments of brain tumors to detect abnormalities in the ROI. The system was able to detect further data imbalances due to the improper edge matching. The data was then analyzed using the algorithm's selectivity parameter. The study was conducted based on the experimental results, which revealed that the system was able to detect brain tumors with a 99.55% accuracy.

G.Hemanth et al.[26] reveals that output generated by this study is clear and precise. It relies on processing every step in the process, which makes it possible to achieve accuracy at the end. Many exiting methods are used in the process, and the ones that offer the best results are selected. This paper presents a method that uses the neural network approach to detect brain tumors. There are various classical approaches to detecting brain tumors, but the present work utilizes the neural network method to detect brain tumors. The CNN algorithm is a powerful tool for detecting brain tumors. It can be used on multiple images and produces the most accurate and effective results. Mahmoud Al-Ayyoub et al.[27] explains various implementation of machine learning algorithm to the applications of medical image classification algorithms, discussed neural network classification performed well after preprocessing MRI images. A better dataset can be achieved by taking advantage of the high-resolution images taken from an MRI scanner.

Detection of tumor using DL

Different network frameworks claim that the brain's M.R. image segmentation can be done using deep learning techniques which shows in fig.6. For instance, CNN's Convolutional Neural Network can be used to classify the images of the brain. On the other hand, the FCN network can be used to classify the images of the brain tumors.

S. Poornam et al.[28] explains reprocessing images will be used to resize them. The dataset grew due to the various modification functions that were performed during the augmentation of brain tumor images. Using ResNet, the network is trained using a deep learning framework. The characteristics of the brain tumor image are used to classify it. The connected layers carry out the classification process. The performance of the system is evaluated using the cross-validation procedure. A brain tumor is a type of cancer. Different terms such as image classification, deep learning, and classification are used to describe how these technologies are used to classify images. This paper presents a deep learning approach that is used to locate the tumor images in brain image. It involves implementing a feature extraction stage, a feature classification stage, and a Gabor transform algorithm. The images are then transformed into time, frequency, and phase orientation pixels in MRI. In order to improve the efficiency of the algorithm, the first step involves extracting statistical patterns from the transformed brain image. The next step is to classify the various features into two categories: meningioma and non-meningioma brain MRI images. These two categories are then classified into mild and severe[29]. A convolutional neural network (ConvNet) efficiently used to diagnose brain tumor, also that can be used to segment gliomas from images taken from a medical image. Works well with BRATS dataset [30].

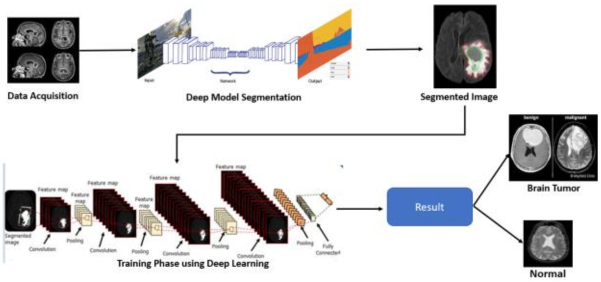

Fig. 7 MRI processing using Deep Learning

ANALYSIS

The paper reviews the current state of the art in machine learning and deep learning-based brain tumor segmentation and discusses the various techniques and research being conducted in the field. It is no surprise that these techniques and methods have become the dominant ones in the field. In the past few years, the use of end-to-end CNNS and a U-Net network for brain tumor segmentation has been widely used. However, even if the same network architecture is used, the results of the segmentation are not the same. This is because the data preprocessing techniques used in the network can improve the accuracy of the segmentation.

Almost all of the research conducted in the field has involved data preprocessing. This review summarizes that the traditional methods are very easy to implement and can handle complex images. However, the accuracy of the segmentation is not the same. Traditional machine learning techniques are easy to understand but are not very effective at processing large data sets. On the other hand, deep learning techniques are more capable of extracting the deep information from an image.

One of the main issues that prevent the implementation of deep learning techniques in the segmentation of brain tumors is the lack of a comprehensive understanding of the various lesions in the image. The processing of multimodal data, which is the primary component of brain tumors, is very important to improve the segmentation's accuracy. Unfortunately, many studies on brain tumor segmentation are only currently being conducted at the theoretical stage. Therefore, they cannot meet the medical staff's needs and are not ideal for clinical practice. Despite the increasing popularity of machine learning and deep learning techniques in the field of brain tumor segmentation, it is still very challenging to implement due to the complexity of the task.

CONCLUSION AND FUTURE DIRECTIONS

This paper aims to summarize the existing segmentation methods and identify their future directions. This project's main areas of focus are the acquisition and processing of data, the calculation of features, and the clinical application of MRI images. Due to the increasing importance of brain tumors in the diagnosis and treatment of cancer, the traditional methods of research have been replaced by the use of data analysis and statistical methods.

The ability to integrate the data of different institutions will greatly improve the accuracy of tumor segmentation. However, it is still not yet clear how to implement a general method to deal with the changes in brain M.R. images generated by different scanners. With machine learning and deep learning, we can perform various tasks such as extracting features, mapping network layers, and solving complex problems. As brain tumor M.R. image data increases, we can obtain high-quality and portable results. This is ideal for applications such as Pytorch and TensorFlow. However, despite the increasing popularity of deep learning techniques, it is still not yet clear how to improve the network's performance in performing segmentation. One of the most important factors that can be considered when it comes to improving the performance of the network is the ability to improve the feature expression.

Currently, the mainstream methods for performing brain tumor segmentation are not able to accurately segment the images due to the complexity of their manual labeling. To improve the performance of the network, the methods must be equipped with unsupervised learning capabilities. One of the most important factors that can be considered is the ability to perform small number of labels. In addition, the increasing number of collaborations between computer scientists and clinicians in the field of medical imaging has resulted in the development of more interdisciplinary solutions. One of the most important factors that can be considered when it comes to developing effective brain tumor segmentation techniques is the ability to integrate the clinical information collected by the system. This will allow the researchers to improve the efficiency of the segmentation process.

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