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A REVIEW: PREDICTION OF TUMOR FROM BRAIN MRIS USING DIFFERENT SEGMENTATION APPROACHES

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Abstract

Technology advancements have the power to impact every area of human existence. Technology has, for instance, significantly benefited human civilization when used in medicine. In this piece, we concentrate on using technology to help treat brain tumors, one of the most prevalent and deadliest illnesses ever. One of the malignant tumors that is identified most often in people of all ages is a brain tumor. Using brain MRI data, the most sophisticated deep learning technique, a CNN (Convolutional Neural Network), was utilized to find a tumor. There are still problems with the laborious training process, however. One of the most difficult components of classifying brain tumors is identifying the kind of tumor and avoiding it. In this paper, we did a thorough analysis of the existing attempts to apply various deep learning techniques to MRI data and identified the domain's current obstacles before identifying possible future approaches. Deep learning networks' exponential expansion has made it possible for humans to handle challenging jobs, even in the intricate area of medicine. This article provides an overview of studies on the segmentation of brain tumors using MRI images published between 2018 and 2023. However, in order for the networks to be highly generalizable and with good performance, applying these models needs a big corpus of data. For researchers in the biological and machine learning sectors, several routes for future study are finally presented.

Index Terms—Review, CNN, Deep Learning, Brain Tumor, Feature based prediction, State of art algorithms, Machine Learning.

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I. INTRODUCTION

A tumor is created when cells grow abnormally and com- bine to produce an unnatural portion that differs in many ways from regular cells. The four different types of tumors include meningioma, pituitary, no tumor, and glioma [17].Finding aberrant growths in the brain, either malignant or not, that may or may not be tumors is the process of ”brain tumor identification.” A patient’s prognosis and quality of life may be considerably enhanced by early identification and treatment, which highlights the significance of brain tumor detection [13]. Due to their sometimes vague symptoms and ability to mimic other neurological diseases, brain tumors may be difficult to identify [7]. However, there has been a rise in interest in leveraging these technologies for more precise and effective brain tumor diagnosis as a result of new imaging methods and advancements in machine learning algorithms [1]. Early identification and planning of therapy are essential for brain tumor patients and may improve their prognosis.

Various imaging methods, such as magnetic resonance imaging (MRI), computed tomography (CT), positron emission tomography (PET), and electroencephalography, are now used to diagnose brain tumors (EEG). These imaging methods are used to view the brain and look for any potential abnormal growths [4]. In addition to imaging methods, machine learn- ing algorithms have drawn increasing attention as a way to increase the precision and effectiveness of brain tumor identi- fication [5]. Large volumes of imaging data may be analyzed by these algorithms to find patterns and characteristics that are suggestive of brain tumors. The identification of brain tumors may still be difficult, despite advancements in imaging and machine learning technology, since certain tumors may not have obvious symptoms or may be hard to tell apart from other neurological diseases. Therefore, there is a constant need for study and the creation of fresh methods to increase the precision and efficiency of brain tumor identification.

This review paper’s objectives are to provide a summary of the status of brain tumor detection today and to explore the many strategies and techniques that have been used. The goal of the article is to emphasize the benefits and drawbacks of the existing approaches for detecting brain tumors and to point out areas that need more study. The review article will also examine how machine learning and deep learning methods are used to the identification of brain tumors and will analyze both their potential advantages and disadvantages. Overall, the goal of the article is to provide readers a thorough grasp of how to identify brain tumors, how important it is to do so, and what research is being done in this area right now.

II. MEDICAL IMAGING HISTORY: BRAIN IMAGING

The practice of medicine known as ”medical imaging” entails the use of a variety of methods to see the body’s interior organs for diagnostic and therapeutic reasons [2] [8]. The use of imaging tools to research the anatomy and function of the brain is one of the most significant uses of medical imaging. X-rays, which enabled medical professionals to see the bone structure of the brain, formed the basis for the early types of brain imaging. The soft tissues of the brain could not be studied with X-rays because of a lack of detail. New imaging methods, such as computed tomography (CT) and magnetic resonance imaging, were created in the middle of the 20th century to enable medical professionals to see the soft tissues

of the brain (MRI).

A 3D picture of the brain is produced by CT scans using X- rays, and they are valuable for finding anomalies like bleeding

or swelling in the brain. MRI scans may

aid in the diagnosis of diseases including brain tumors, stroke, and dementia by producing very fine-grained pictures of the brain's soft tissues using magnetic fields and radio waves.

Functional imaging methods may aid in determining the regions of the brain that are engaged during certain activities or under particular circumstances, in addition to these structural imaging methods. For instance, functional magnetic resonance imaging (fMRI) and positron emission tomography (PET) are effective for determining the areas of the brain that are engaged during cognitive activities and for examining the functional structure of the brain.

Overall, brain imaging has made a substantial contribution to our knowledge of the anatomy and function of the brain and is a useful tool for the diagnosis and treatment of a variety of neurological diseases.

A. Brain Anatomy

The term "brain anatomy" describes the arrangement and structure of the brain. Movement, sensation, perception, and thinking are just a few of the numerous bodily processes that the brain regulates [3]. It is made up of many functionally distinct sections linked by a web of nerve fibres.

The cerebellum, the brainstem, and the cerebrum are the three major components of the brain. Two hemispheres make up the cerebrum, the biggest portion of the brain (left and right). The frontal, parietal, temporal, and occipital lobes make up each of each hemisphere's four divisions [9]. Conscious cognition, sensation, and voluntary movement are a few of the numerous processes that the cerebrum is in charge of. The area of the brain that joins the spinal cord and cerebrum is known as the brainstem. The pons, midbrain, and medulla oblongata make up its three constituent sections. Numerous bodily processes that happen automatically, such as breathing, heart rate, and digestion, are controlled by the brainstem. Underneath the cerebrum and beneath the brainstem is where the cerebellum is found. It controls how the body moves and maintains its equilibrium.

Neurons and glial cells are only two of the many kinds of cells that make up the brain. Specialized cells called neurons are able to connect with one another and transfer electrical impulses [4]. Glial cells maintain and guard the neurons in addition to contributing to brain activity.

The cerebrospinal fluid that surrounds and cushions the brain and aids in maintaining a stable environment for it, as well as the skull, which protects it, assist keep it in a healthy state. The internal carotid and vertebral arteries, which are a part of the cerebral circulation, provide additional blood flow to the brain. For the brain to get oxygen, nutrients, and waste products as well as to be able to remove them, blood flow is crucial.

Overall, the brain's architecture is intricate and diverse, and it is in charge of many essential bodily processes. For the diagnosis and treatment of neurological diseases, an understanding of the anatomy of the brain is necessary.

B. Anomalies in the Brain

Brain structural or functional anomalies are referred to as anomalies in the brain. These anomalies, which may be brought on by a variety of factors such as genetic mutations, developmental problems, infections, traumas, and illnesses, may impact different areas of brain function.

Typical instances of brain abnormalities include:

1. Anomalies of structure: Anomalies in the size, shape, or organization of the brain's structures are referred to as structural anomalies. Brain abnormalities, such as microcephaly, in which the brain is

smaller than usual, or holoprosencephaly, in which the two hemispheres of the brain fail to separate cor- rectly, may be caused by aberrant brain growth during foetal development. Injuries to the brain tissue, such as contusions, hematomas, or skull fractures, may potentially cause structural malformations.

2. Defects in functionality: Neurotransmitter imbalances or changes in neuronal activity patterns are examples of func- tional anomalies, which are deviations from normal brain function. Mood disorders like sadness and anxiety, which are linked to imbalances in neurotransmitter levels, and epilepsy, in which aberrant electrical activity in the brain results in convulsions, are a few examples of functional abnormalities.

3. Tumors: The abnormal proliferation of brain cells is known as a brain tumor [10]. They may develop from glial cells, neurons, and meningeal cells among other kinds of brain cells, and they can be benign or cancerous. According on their size and location, tumors may produce a variety of symptoms, but if they are not treated, they can cause death or severe brain damage.

4. Traumatic Brain Injury (TBI): A traumatic brain injury (TBI) is a brain damage brought on by an external force, such as a blow to the head or a piercing wound. Depending on the extent of the damage, a TBI may cause a variety of symptoms, including long-term abnormalities in cognition and behavior [28].

5. Virus-borne illnesses: Meningitis, encephalitis, and neu- rosyphilis are just a few examples of the infectious disorders that may harm the brain. Inflammation, brain tissue destruc- tion, and a variety of neurological symptoms may all be brought on by these illnesses.

In general, brain abnormalities may have a significant influ- ence on how well the brain functions and can cause a variety of neurological and cognitive problems. These abnormalities of- ten need a multidisciplinary approach combining neurologists, neurosurgeons, and other experts, as well as a mix of medical imaging, genetic testing, and other diagnostic techniques.

III. BRAIN TUMOR LOCALIZATION AND DIAGNOSTIC PROCEDURES

Critical first stages in the treatment of brain tumors are the location and diagnosis of the tumor. During these operations, the tumor’s nature, location, size, and possible effects on brain function are all identified.

Brain tumors may be located and diagnosed using a variety of techniques, such as:

1. Magnetic Resonance Imaging (MRI): The brain is seen in

great detail using the noninvasive imaging method known as magnetic resonance imaging (MRI). When diagnosing brain tumors, it is the most often utilized imaging technique. Brain tumors may be found via MRI, which can also provide details about their composition, location, size, and other characteris- tics [11].

2. Computed Tomography (CT) Scan: The brain is imaged during a CT scan using X-rays. They may help detect the existence of tumors and provide details about their size and location. In comparison to MRI, CT scans are quicker and less costly, but they are less sensitive in identifying certain forms of brain cancers.

3. Positron Emission Tomography (PET) Scan: To find metabolic activity in the brain, PET scans employ a radioactive tracer. They may be used to determine if a brain tumor is present and to provide details on its metabolic activities.

4. Biopsy: An operation known as a biopsy involves the surgi- cal removal of a sample of brain tissue to be microscopically analyzed. The kind and grade of a brain tumor are usually

determined by a biopsy, which is often used to confirm the diagnosis.

5. Examining the nervous system: A neurological examination includes testing the patient's reflexes, muscular power, coor- dination, and sensory perception as well as their neurological health. About the tumor's location and size, this might provide crucial information.

6. Testing for Neuropsychology: The patient's cognitive and behavioral function is evaluated during neuropsychological testing. Insightful data on the tumor's effect on brain function may be obtained from this.

Overall, imaging, biopsy, and clinical evaluation are often used to localize and diagnose brain tumors. For patients with brain tumors, these procedures are essential for directing therapy choices and enhancing results [27].

IV. SOURCES OF DATA AND A SEARCH PROCESS

Brain tumor segmentation remains one of the most dif-

ficult jobs in medical imaging because of their unexpected appearance and form [19]. About 28 research publications from the years 2018 to 2023 were analyzed for this report. These approaches for finding brain tumors were created and tested on a number of well-known datasets [TABLE 1].

BraTS2016 is a benchmark dataset and challenge for the segmentation and classification of brain tumors. The BraTS2016 dataset consists of MRI images of 274 people who have brain tumors as well as manually segmented tumors that were done by skilled medical professionals. Participants in the competition were charged with creating and analyzing algorithms for automatically segmenting and categorizing tu- mors using this information [18]. In order to test and evaluate brain tumor segmentation and classification algorithms, the BraTS2016 competition, which was followed by other chal- lenges in later years, was extensively utilized in the medical imaging and machine learning research fields.

Brain tumor segmentation and classification benchmark dataset and competition called BraTS2017. The Medical Image Computing and Computer Assisted Intervention (MICCAI) Society sponsored the "Multimodal Brain Tumor Segmenta- tion Challenge." Its full name is this. The BraTS2017 dataset consists of MRI images of 285 people that have brain tumors as well as manually segmented tumors that were done by skilled medical professionals. Participants in the competition were charged with creating and analyzing algorithms for automatically segmenting and categorizing tumors using this information [26]. Many brain tumor segmentation and classi- fication algorithms have been evaluated and compared using the BraTS2017 challenge in the fields of medical imaging and machine learning.

The BraTS2018 dataset, in a similar vein, comprises manual tumor segmentations made by knowledgeable doctors coupled with Magnetic Resonance Imaging (MRI) images of 285 individuals with brain tumors. Participants in the challenge were charged with creating and analyzing algorithms for automated tumor segmentation and classification based on this dataset. By adding two additional tasks—the segmentation of tumor invading the brain parenchyma and the prediction of patient overall survival—the BraTS2018 challenge broadened the scope of prior challenges.

"Ischemic Stroke Lesion Segmentation" competition is known as ISLES-2018. By recognizing and defining areas of the brain that have been impacted by an ischemic stroke on Magnetic Resonance Imaging (MRI) images, the challenge intended to enhance the state-of-the-art in ischemic stroke lesion segmentation. 43 MRI images from individuals who had just had an acute ischemic stroke were made available as part of the ISLES-2018 challenge, coupled with manual segmentations of the lesions done by skilled medical professionals. Participants in the competition were charged with creating and analyzing automated stroke lesion segmentation algorithms based on this dataset. The ISLES-2018 competition, which was followed by several challenges the following year, was extensively utilized in the machine learning and medical imaging research fields to test and evaluate stroke lesion segmentation algorithms.

V. MRI BRAIN TUMOR SEGMENTATION COMPLEXITY PROBLEMS

For the segmentation of brain tumors, Magnetic Resonance Imaging (MRI) is a popular method. Identifying and separating tumor areas from healthy brain tissue on MRI images is a tech- nique known as segmentation [24]. Brain tumor segmentation using an MRI offers numerous benefits, but it also has some drawbacks. MRI brain tumor segmentation presents a number of difficulties, such as:

1. The variety of malignancies: Different levels of cellularity, necrosis, edoema, and contrast enhancement may be present in heterogeneous brain tumors. Particularly in places with minor alterations, this heterogeneity may make it difficult to distinguish precisely between tumor and normal brain tissue.

2. Traces of an image: Motion artefacts, inhomogeneities in the magnetic field, and picture noise are just a few of the abnormalities that may interfere with MRI images. By producing incorrect tumor area categorization, these artefacts

TABLE I

SOURCE OF DATABASE AND METHODS

Source Databases	**Method(s)**	**Papers**
BraTS2015	Quantitative Survey	[R8], [R9]
BraTS2016	Assisted Quadratic Logit BoostClassifier (DBNQLBC)	[R1], [R28]
BraTS2017	Convolutional XGBoost (C-XGBOOST), K-nearest neighbor, Featuresand Extreme Learning Machine (ELM)	[R5], [R10], [R17]
BraTS2018	VGG16 , VGG19, 3D CNN, Discreate Wavelet Transform (DWT), Deep CNN	[R2], [R11], [R18], [R19], [R20]
BraTS2019	K-Means Clustering, Cascade Convolutional Network	[R3], [R25]
ISLES-2018	CNN and SVM	[R23]
MRI Dataset from Figshare	Deep CNN, R-CNN	[R14], [R21]

Iranian Imaging Center	CNN and Softmax	[R13], [R27]
MICCAI 2013	Marker Based Watershed Algorithm	[R12]
WBA Dataset	Five Layers Stopping Criteria and Batch Normalization	[R16]
The Cancer Imaging Archive	CNN with U-Net Segmentation	[R15]
BraTS2020	U-Net Architecture, DeepLab V3 Model	[R22], [R24], [R26]

might affect the segmentation algorithms' accuracy.

3. Different imaging procedures: The imaging procedures T1- weighted, T2-weighted, and FLAIR may all be used to obtain MRI images. Choosing a procedure may impact how well a tumor is segmented since each technique offers a different level of information about the tumor.

4. Absence of reality: For tumor segmentation, there is often no baseline or industry-accepted gold standard. As a con- sequence, comparing the findings of various research and assessing the precision of segmentation algorithms is difficult.

5. Complexity of computation: It takes a lot of computing power and memory to segregate brain tumors using an MRI, which is a computationally challenging operation. Applica- tions of segmentation algorithms in healthcare contexts could be constrained by processing times.

6. Patterns of tumor development: The location of the tumor, the patient's age, and other clinical parameters may all have an impact on the development pattern of brain tumors [21]. De- veloping segmentation algorithms that can precisely recognize cancers of various forms and at various phases of development may be challenging due to these variances.

In general, the difficulties associated with MRI brain tumor segmentation underscore the necessity for the creation of reliable and precise segmentation algorithms that can take into account the variety of brain tumors and get beyond the constraints of MRI imaging [20].

VI. PERFORMANCE ANALYSIS

A popular statistic for assessing segmentation performance is intersection over union (IoU). It calculates the degree to which the expected segmentation and the segmentation based on the ground truth overlap. A complete overlap between the two segmentations is indicated by a score of 1, which is scaled from 0 to 1. The proportion of properly identified pixels in the picture is quantified by the statistic known as ”pixel accuracy.” By dividing the number of pixels in the picture that were properly identified by all of the pixels in the image, it is determined.

Recall indicates the proportion of true positives in the segmentation that was done using the actual data, whereas precision measures the percentage of true positives in the segmentation that was done using the projected data. These metrics may be used to assess how well segmentation models perform on certain kinds of images. It is usual practice to measure segmentation performance using the F1 score, which is a weighted average of accuracy and recall. It has a 0 to 1 scale, with 1 denoting ideal performance [22].

Processing speed, memory utilization, and the capacity to generalize to fresh pictures are other aspects that may be taken into account when assessing segmentation performance in addition to these measures. To assess the overall effectiveness of an image segmentation model, it is crucial to take these variables into account in addition to the assessment metrics.

VII. CONCLUSION

A difficult challenge in cancer diagnosis is the automatic segmentation of brain tumors. The segmenting of brain tumors from MRI using cutting-edge data augmentation techniques was the focus of this work. We thoroughly examined the WBA Dataset, MICCAI 2013, the MRI Dataset from Figshare, all of the BraTS Database challenges, and ISLES-2018, and we examined the segmentation and prediction algorithms used in these systems. Due to their ease of use and ability to create anatomically accurate brain tumor instances, affine transforma- tions continue to be the most used in practice, according to our analysis. We reviewed cutting-edge deep learning techniques in this article and gave a quick rundown of more conventional approaches. Selecting highly representative features for classi- fiers or converting past information into probabilistic maps is a difficult challenge in conventional automated tumor classes segmentation systems. The development of clinically accept- able automated tumor segmentation techniques for improved diagnosis may result from future changes and enhancements to CNN designs and the integration of supplementary data from other imaging modalities.

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