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Brain Tumor Detection using Deep Learning

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Abstract:** A tumor is an abnormal swelling or growth that is caused by the division of the cells in the nervous system. A brain tumor is one of the most dangerous types of tumors. There are four different types of brain tumor. The treatment for brain tumors is determined by the type, grade, and locationof the tumor. If the tumor is not detected early, it can be fatal. MRI images are used to diagnose brain tumors. The accuracy of the results depends on the expertise and domain knowledge of the experts, and it is also a very time-consuming and costly process. In order to overcome these limitations, several deep learning algorithms for the detection of brain tumors have been proposed. This review paper provides an in-depth and comprehensive guide to this subfield of brain tumor detection, focusing mainly on segmentation and classifying the brain tumor. It compares and summarizes the latest research in this domain, comparing and summarizing 25 research papers. The research work makes a comparison between the state-of-the- art approaches and highlights the differences between them. The purpose of the survey is to provide an overview of MRI modalities and to discuss common techniques for segmentationof brain tumors from MRI images. This includes the use of deep learning techniques to segment brain tumors and themost significant advances in this field that have been made in recent years. In summary, we focused on the fundamental building blocks of CNN algorithms used to segment images. In the entirety of the review methodology, hybrid techniques as well as CNN based segmentation have been found to be more effective for segmentation from brain tumor images. There is alot of research going on in this field, and this paper would help all future researchers.

***Keywords:** Brain Tumor Detection, MRI, Image Processing Techniques, Deep Learning, Convolutional Neural Networks (CNNs).*

I. INTRODUCTION

The human brain, often regarded as the epicenter of nervous activity, stands as one of the body's most vital yet intricate organs. Addressing issues related to the brain, particularly those involving brain tumors, poses significant challenges in the field of medicine. Each year, approximately 350,000 new cases of brain tumors emerge worldwide, casting a shadow over the lives of those diagnosed. With a five-year survival rate of just 36% for brain tumor patients, the urgency of finding effective diagnostic and treatment solutions is undeniable [1].

Brain tumors are categorized as either benign (non- cancerous) or malignant (cancerous), and their severityvaries from Grade I to Grade IV according to the World Health Organization (WHO) classification [8]. Neurosurgery is often recommended as the primary treatment for brain tumors. However, in advanced stages, when surgical intervention becomes less viable, alternative strategies involving radiation and chemotherapy come to the forefront, aiming to halt or slow the growth of cancerous cells [5].

The high fatality rate associated with brain tumors underscores the critical importance of early detection for effective treatment. Various medical imaging techniques, such as Positron Emission Tomography (PET), Magnetic Resonance Imaging (MRI), and Computed Tomography (CT), play a pivotal role in diagnosis [3]. Among these techniques, MRI stands out as a particularly effective tool for examining soft tissues and the nervous system, offering high-resolution, detailed images without the use of damaging X-ray radiation [6, 7].

However, interpreting MRI images is not without its challenges, as similar behaviors in different parts of thebrain can lead to misdiagnoses. With tens of thousands of individuals diagnosed with brain tumors annually, the application of deep learning techniques for automatic detection and classification of these tumors has garnered considerable interest. Furthermore, these techniques have found utility in the segmentation of brain tumors, a field of growing importance within the medical community [6]. Segmentation aims to enhance the interpretation of differentimage areas, making distinct regions with unique characteristics more discernible and spatially contiguous, offering a promising avenue for improved diagnostic and treatment outcomes [1, 2].

II. LITERATURE SURVEY

Research work by 10 different authors has been discussed on the basis of varied deep learning techniques and architectures adopted by them.

In the study conducted by Sakshi Ahuja and her colleagues [1], transfer learning in conjunction with the superpixel technique was employed to detect brain tumors and performbrain segmentation. The dataset utilized for this research originated from the BRATS 2019 brain tumor segmentation challenge, and the model was trained based on the VGG 19 transfer learning model. By applying the superpixel technique, the tumors were delineated, distinguishing between low-grade glioma (LGG) and high-grade glioma (HGG) images. This approach yielded an average Dice index of 0.934 when compared to the ground truth data.

Hajar Cherguif and her team [2] harnessed the power of U- Net for the semantic segmentation of medical images. They constructed an effective 2D segmentation network using the U-Net architecture. The BRATS 2017 dataset served as the testing and evaluation benchmark for their model. The U-Net architecture they put forward featured a total of 27 convolutional layers and 4 deconvolutional layers, ultimately achieving a Dice coefficient of 0.81.

Chirodip Lodh Choudhury and their collaborators [3] harnessed the potential of deep learning techniques, incorporating deep neural networks alongside a Convolutional Neural Network (CNN) model to enhance the precision of MRI scan analysis. They introduced a 3- layer CNN architecture, which was seamlessly integrated with a Fully Connected Neural Network. This innovative approach yielded remarkable results, with an F-score of 97.33 and an impressive accuracy rate of 96.05%. [3]

In a study conducted by Ahmad Habbie and colleagues [4], MRI T1 weighted images were obtained, and a semi- automatic segmentation approach was employed to assess the potential presence of a brain tumor. The study evaluated the performance of three distinct segmentation methods: morphological active contour without edge, snake active contour, and morphological geodesic active contour. Among these techniques, the data analysis revealed that morphological geodesic active contour (MGAC) outperformed the other two, suggesting its superior performance in this context. [4]

In their research, Neelum and colleagues [5] adopted a concatenation approach in their deep learning model to analyze the likelihood of brain tumors. They leveraged pre-trained deep learning models, specifically Inception-v3 and DenseNet201, for the detection and classification of brain tumors. The Inception-v3 model was pre-trained to extract pertinent features, and these extracted features weresubsequently concatenated for tumor classification. Theclassification process was executed using a softmax classifier.[5]

In their study, Ms. Swati Jayade and her collaborators [6] employed a hybrid classifier approach to categorize tumorsinto two main types: malignant and benign. They prepared a feature dataset using the Gray Level Co-occurrence Matrix (GLCM) feature extraction method. To enhance efficiency, the researchers proposed a hybrid classification method that combined K-Nearest Neighbors (KNN) and Support Vector Machine (SVM) classifiers. This combined approach aimed to improve the overall classification performance.[6]

In the study conducted by Zheshu Jia and colleagues [7], the authors developed a fully automated heterogeneoussegmentation approach, incorporating Support VectorMachine (SVM) for their analysis. To assess the accuracy of tumor detection in MRI images, a classification system based on the probabilistic neural network was employed for training and validation. The research used a multispectral brain dataset and placed particular emphasis on the automated segmentation of meningioma, a type of brain tumor.[7]

In their research, Dr. Akey Sungheetha and Dr. Rajesh Sharma R. [8] applied a combination of Gabor transform and both soft and hard clustering techniques for edge detection in CT and MRI images. A substantial dataset was used, comprising 4500 instances of MRI images and 3000 CT images. K-means clustering played a pivotal role in segregating similar features into sub-groups. To represent the images using histogram properties, the authors opted for the Fuzzy C-Means clustering method.[8]

In their study, Parnian Afshar and her team [9] adopted a Bayesian approach for the classification of brain tumors, employing capsule networks instead of traditional Convolutional Neural Networks (CNNs). The rationale behind this choice was to preserve essential spatial information that CNNs might lose. The researchers introduced the BayesCap framework to enhance the accuracy of tumor detection. To assess the effectiveness of their model, they utilized a well-established benchmark brain tumor dataset.[9]

In this Paper Yuan Wang an Team[10] Implemented F2 FCN it was used in order to operate the pixel wise brain tumor segmentation. x A feature reuse model was introduced in order to make the reuse rate of valuable features better [10].

III. BRAIN TUMOR DETECTION

The brain, an intricately complex organ, comprises approximately 100 billion neurons and plays a pivotal role in sensory integration, motor responses, and the center of learning. Within the human body, the Central Nervous System (CNS), consisting of the brain and the spinal column, holds responsibility for overseeing vital functions, encompassing thought, speech, and body movements. Brain tumors, characterized by abnormal cell proliferation, can disrupt the body's normal operations, impacting a person's speech, mobility, and cognitive processes. There exist two primary types of brain tumors: primary and secondary. Primary tumors originate within the brain and can be further categorized as low-grade or high-grade, with low-grade tumors exhibiting slower growth rates. In contrast, secondary brain tumors are cancerous, originating from a different part of the body and subsequently metastasizing to the brain [2].

The brain's intricate structure renders the diagnosis of brain tumors a challenging endeavor. These tumors claim the lives of nearly 250,000 individuals each year. Accurate diagnosis, however, offers a glimmer of hope in extending the lives of those affected. Magnetic Resonance Imaging (MRI) plays a prominent role in brain tumor detection. The process of detecting and treating brain tumors entails the following steps:

A. Pre-processing

The initial step in brain tumor detection involves pre- processing raw MRI images. The purpose is to enhance image quality and make them suitable for human or machine analysis. Pre-processing also serves to eliminate unwanted noise and improve the overall appearance of MRI images. Techniques include loading image datasets into arrays, resizing images to a standardized size, normalizing pixel values, and data augmentation to expand the dataset's size if the number of images is insufficient. These steps, as outlined in [9, 8], significantly enhance classification accuracy and accelerate the training process.

B. Skull Stripping

Skull stripping is the process of removing non-braintissues from the images, leaving only the cerebral tissue relevant for brain tumor analysis. This step eliminates unnecessary elements like fat or skin [8]. Common techniques for skull stripping are based on imagesegmentation and contouring.

C. Segmentation

Segmentation aims to distinguish abnormal brain tissue from the normal brain tissue. There are three primary segmentation techniques: manual, semi-automatic, and fully automatic [2]. Manual segmentation involves manually tracing the affected tissue's outline, offering the highest accuracy but also being time-consuming. Semi- automatic segmentation requires user input for initial data, while fully automatic methods do not necessitate manual parameter setting, automatically detecting and segmenting the brain tumor.

D. Feature Extraction

Feature extraction enhances system accuracy by selecting prominent features for analysis. It acts as a method for reducing data dimensionality, converting the initial data into a more manageable format for processing.

E. Post-processing

Post-processing provides insights into the tumor area of the brain image. It includes methods like imposing shape limits on samples, context-based constraints for improved accuracy, and spatial control. Post-processing techniques aim to refine the analysis of the brain image's tumor region.

Brain scans, predominantly through MRI, are commonly employed for tumor detection. This paper discusses proposed algorithms based on MRI scans, categorizing brain tumors into three broad types:

1) *Benign Tumor:* Benign tumors are non-cancerous and do not spread to other body parts or invade adjacent tissues. They grow slowly but can cause complications by compressing nerves, obstructing blood flow, or crowding normal brain regions. In most cases, benign tumors respond well totreatment and can be surgically removed. They typically have a low chance of recurrence [7].

2) *Pre-malignant Tumor:* Benign tumors may or may not become cancerous. Continual uncontrolled cell proliferation can lead to malignancy. Pre-malignant tumors necessitate careful monitoring for changes in cell characteristics, such as cell appearance and growth rate.
3) *Malignant Tumor:* Malignant tumors are cancerous and have the potential to invade nearby tissues. Cancerous cells can break away from the tumor, spreading to other parts of the body through the lymphatic system or bloodstream, a process known as metastasis [2]. Malignant tumors grow rapidly, can recur, and may require aggressive treatments such as chemotherapy, radiation, and surgery. They pose a significant threat to health and demand prompt intervention.

IV. IMAGE SEGMENTATION

Image Segmentation involves the division of images into constituent segments or regions, facilitating the detection of objects and edges within the images. This partitioning is based on the characteristics of individual pixels in the image [6, 1]. The segmentation process may involve separating the foreground from the background or grouping together pixels with similar shapes and colors. In medical imaging, Image Segmentation plays a crucial role and is widely applied. Several common segmentation techniques include:

A. Threshold-Based Segmentation

This is a straightforward segmentation technique that assigns pixels in the image either black or white values. It involves comparing the pixel value with a threshold value. If the pixel value is lower than the threshold, the pixel is set to black; otherwise, it's set to white. The threshold value can be adjusted as needed. This method is commonly used for separating foreground from background, but it only offers a binary division. It is particularly useful when objects of interest exhibit higher intensity than the background or unwanted portions of the image.

B. Edge-Based Segmentation

Edge-based segmentation aims to detect edges within an image, which can subsequently be used to identify specific objects. Two common edge segmentation algorithms are the Sobel and Canny edge detection algorithms [8].

C. Clustering-Based Segmentation

Clustering-based segmentation creates segmented images through an initial rough pixel clustering. Using gradient ascent methods, these clusters are refined until the image is effectively segmented. These methods work to minimize the distance between pixels and the formed clusters [4, 8]. Common clustering algorithms include K- means clustering, SLIC (Simple Linear Iterative Clustering), and watershed segmentation, among others.

D. Graph-Based Segmentation

In graph-based segmentation, individual pixels are treated as nodes within a graph. The similarity between adjacent pixels is reflected in the edge weights connecting these graph nodes. This set of nodes and edges allows pixels to be grouped into superpixels or distinct segments. Common graph-based segmentation techniques include Graph Cut and Normal Cut [4, 8].

These segmentation techniques serve diverse purposes in image analysis and are applied according to the specific characteristics and requirements of the images under consideration.

V. CONCLUSION

This paper introduces the concept of brain tumor detection and segmentation and highlights and compares some of the key points of state-of-the-art approaches used in this domain. Some of the commonly used techniques are ML techniques like Fuzzy K-means clustering and Random Forests, as well as the use of CNN architectures is prevalent. In particular, Chirodip Chaudhary et al. [3] achieved the highest accuracy of 97.33% with the use of MKSVM algorithm on the MMRI dataset. High accuracy of classification of 96.03% was also achieved through the use of a combination of feature extraction algorithm and CNN [2]. There are a few challenges encountered in further research work in this domain. Deep learning methods require large datasets for training purposes, and the lack of such large publicly available datasets is an obstacle. There is a scope for increase in the number of available datasets and improved access to them to aid future research work in this domain. Researchers have requested experts in this domain, such as neurologists and radiologists, to prepare structured labelling reports to aid further research.

Another common issue is the presence of class imbalances in the types of tumor. This issue is commonly tackled through the use of data augmentation techniques by rotating or scaling down existing images [3]. At present, the majority of deep learning methods involve classification of tumor area, but the anatomical location of tumor region is not known to the network. Further research work in this domain can be directed towards incorporating this information in the neural network, possibly by feeding the entire image to thenetwork. However, the size of brain tumor images aregenerally of high resolution and in the range of gigapixels, making the training of the network on such images unfeasible due to memory and computational power constraints.

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