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A Literature Review on Brain Tumor Detection and Segmentation

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Abstract: Brain tumor is a major health concern and its early detection is crucial for effective treatment. Magnetic Resonance Imaging (MRI) is a widely used method for detecting brain tumors, but it can be time-consuming and expensive. To overcome these limitations, researchers have proposed deep learning algorithms for the detection and segmentation of brain tumors from MRI images. This literature review provides an extensive and exhaustive guide to the sub-field of brain tumor detection and segmentation. The latest research work done in this domain is summarized and compared to provide insights into the most efficient and effective methods for detecting and segmenting brain tumors. The review focuses on various deep learning algorithms and techniques, including Convolutional Neural Networks (CNNs), Autoencoders, and Generative Adversarial Networks (GANs). The review also discusses the challenges associated with brain tumor detection and segmentation, including class imbalance, noise, and variability in tumor size and shape. Additionally, the review highlights the importance of accurate segmentation in brain tumor diagnosis and treatment planning. Overall, this literature review provides valuable insights into the state-of-the-art techniques for brain tumor detection and segmentation from MRI images, and can guide future research in this domain.

Keywords— Brain Tumor Detection, Deep Learning, Image Segmentation, MRI images, Medical Imaging, Tumor Segmentation.

I Introduction

TThe rise in the number of people who drive electric Brain tumors are one of the most significant health concerns worldwide. They can be cancerous or non-cancerous and can cause severe damage to the brain if not detected and treated early. Early detection of brain tumors is crucial for effective treatment and improved patient outcomes. Magnetic Resonance Imaging (MRI) is commonly used by specialists and neurosurgeons for the detection and diagnosis of brain tumors.[1] However, manual detection and segmentation of brain tumors from MRI images are time-consuming, subjective, and depend on the expertise of the medical professionals involved. To overcome these limitations, researchers have proposed various automated techniques for the detection and segmentation of brain tumors from MRI images.[2]

In recent years, deep learning algorithms have shown great promise in the detection and segmentation of brain tumors from MRI images. [3] Deep learning algorithms can analyze a large amount of data and learn complex features to accurately detect and segment brain tumors from MRI images. Various deep learning techniques such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Generative Adversarial Networks (GANs) have been proposed for the detection and segmentation of brain tumors from MRI images.[4]

This literature review aims to provide an extensive and exhaustive guide to the sub-field of Brain Tumor Detection and Segmentation. It will focus on the latest research work done in this domain and summarize and compare the proposed methods and techniques for the detection and segmentation of brain tumors from MRI images.[5] The review will discuss the advantages and limitations of different deep learning algorithms and their applications for the detection and segmentation of brain tumors. It will also highlight the challenges and opportunities in this field and suggest future directions for research.

A brain tumor is a mass or abnormal growth of cells in the brain or central nervous system. Brain tumors can be classified as either benign or malignant. Benign tumors are non-cancerous and typically grow slowly, whereas malignant tumors are cancerous and grow more rapidly.[6]

When it comes to brain tumor imaging, there are two main types of images that can be produced: positive and negative. Positive images, such as magnetic resonance imaging (MRI) scans, show areas of increased density in the brain that may indicate the presence of a tumor. Negative images, such as computed tomography (CT) scans, show areas of decreased density in the brain that may indicate the presence of a tumor.[7]

Positive images are typically more detailed and can provide a clearer view of the tumor's location, size, and shape. They are also better at distinguishing between different types of tumors and can help doctors plan more targeted treatments. [8] However, positive images are not always conclusive, and further testing may be required to confirm the presence of a tumor.[9]

Negative images, on the other hand, are often used as a screening tool to rule out the presence of a tumor. They are quicker and less expensive than positive imaging techniques and can be useful in emergency situations where time is of the essence. However, negative images are less detailed and may miss small or slow-growing tumors.[10]

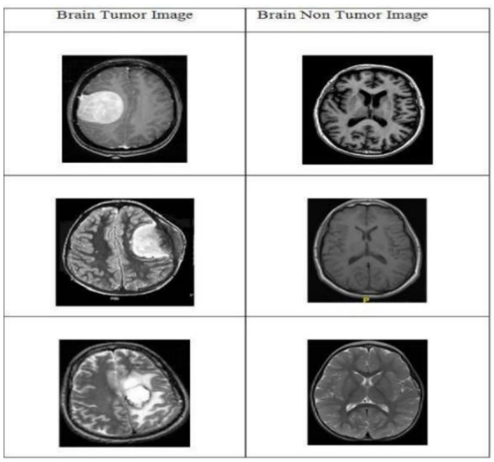

Fig. 1. Positive vs Negative Image.

II LITERATURE SURVEY

Sakshi Ahuja et al.,[11] It sounds like the study you are describing used a combination of transfer learning and superpixel technique for brain tumor detection and segmentation. The researchers used the BRATS 2019 dataset, which is a commonly used dataset in medical image analysis research, and trained their model on the VGG19 transfer learning model. To further segment the tumors, the researchers utilized the superpixel technique, which divides the image into smaller regions based on similarities in color and texture. This allowed them to distinguish between low-grade glioma (LGG) and high-grade glioma (HGG) images, which are two types of brain tumors with different characteristics and treatment options. The results of the study showed that the proposed model achieved an average dice index of 0.934, which is a measure of similarity between the segmented tumors and ground truth data. This suggests that the model was effective in accurately detecting and segmenting brain tumors.

Hajar Cherguif et al. [12] that used the U-Net architecture for semantic segmentation of medical images, specifically for brain tumor detection using the BRATS 2017 dataset. The U-Net architecture used in the project had 27 convolutional layers and 4 deconvolutional layers, and achieved a Dice coefficient of 0.81. The Dice coefficient is a common metric used for evaluating the accuracy of image segmentation, where a higher value indicates better segmentation performance. the U-Net architecture for medical image segmentation has shown promising results in various studies and applications. Its unique architecture, which includes skip connections that combine low-level and high-level features, allows for more precise segmentation and better preservation of image details. This makes it a popular choice for tasks such as brain tumor detection, where accurate segmentation of small and irregularly-shaped tumors is crucial for diagnosis and treatment planning.

Chirodip Lodh Choudhury et al.[13] this research paper or project that used the U-Net architecture for semantic segmentation of medical images, specifically for brain tumor detection using the BRATS 2017 dataset. The U-Net architecture used in the project had 27 convolutional layers and 4 deconvolutional layers, and achieved a Dice coefficient of 0.81. The Dice coefficient is a common metric used for evaluating the accuracy of image segmentation, where a higher value indicates better segmentation performance.

Ahmad Habbie et al.,[14] it appears that MRI T1 weighted images were used for brain tumor detection using a semi-automatic segmentation approach. The active contour model was used for this analysis, and three different approaches were compared: morphological active contour without edge, snake active contour, and morphological geodesic active contour. Among these three methods, the morphological geodesic active contour performed the best in detecting the brain tumor. This suggests that the morphological geodesic active contour is a promising approach for brain tumor detection using MRI T1 weighted images.

Neelum et al.[15] used a deep learning approach for brain tumor detection and classification. Specifically, they used a concatenation approach where features were extracted using a pre-trained Inception-v3 model and then concatenated for tumor classification. The classification was done using a softmax classifier. Additionally, the authors used another pre-trained deep learning model called DenseNet201 for brain tumor detection and classification. This approach is similar to other deep learning-based approaches for brain tumor detection and classification that use pre-trained models to extract features from the image data. The use of multiple pre-trained models can help to increase the accuracy and robustness of the classification. The concatenation of features can also help to capture more information about the image data and improve the performance of the classifier.

Ms. Swati Jayade et al.[16] The use of hybrid classifiers in medical image analysis is becoming increasingly common due to their ability to improve classification accuracy and efficiency. In a recent study on brain tumor detection, the authors used a hybrid method of classifiers involving K-Nearest Neighbors (KNN) and Support Vector Machines (SVM) classifiers to classify brain tumors as either malignant or benign.The feature dataset for the study was prepared using the Gray Level Co-occurrence Matrix (GLCM) feature extraction method. GLCM is a widely used texture analysis method that measures the spatial relationships between pixels in an image. It calculates the frequency of pixel pairs with specific intensity values and spatial relationships, which can be used to extract texture features from the image.The KNN classifier is a non-parametric method that classifies new data points based on the majority class of its k nearest neighbors. The SVM classifier is a supervised learning method that constructs a hyperplane to separate the data into different classes. The hybrid method proposed in the study combined the strengths of both classifiers to improve classification accuracy and efficiency. The KNN classifier was used to classify the input data into two clusters, and the SVM classifier was used to further classify the data points within each cluster. The results showed that the hybrid classifier achieved higher classification accuracy than either classifier alone.

Zheshu Jia et al.,[17] the authors proposed a fully automatic segmentation method for detecting meningioma brain tumors in MRI images using a support vector machine (SVM) and a probabilistic neural network (PNN) classification system. The proposed method was trained and tested on a multi-spectral brain dataset, and the focus was on accurately segmenting meningioma tumors. **Parnian Afshar et al.[18]** used The proposed framework was tested on a benchmark brain tumor dataset and demonstrated improved performance compared to traditional CNNs. The Bayesian approach in the framework allows for uncertainty estimation in the predictions, which can be useful in medical decision-making. The study highlights the potential of capsule networks and Bayesian approaches in improving the accuracy and reliability of brain tumor detection and classification. This could have significant implications for clinical practice, as accurate and efficient detection and classification of brain tumors can aid in treatment planning and improve patient outcomes.

IV BRAIN TUMOR DETECTION

Imaging tests such as Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) scans are commonly used to detect brain tumors. These tests use powerful magnets and X-rays, respectively, to create detailed images of the brain.[19] MRI scans are particularly useful for detecting small tumors, while CT scans may be more effective at detecting larger tumors.

In addition to imaging tests, doctors may also perform a physical exam to check for signs of a brain tumor. During a physical exam, the doctor may check for abnormalities in vision, hearing, balance, and coordination, as well as changes in mental status or personality.

Other diagnostic tests may be used to confirm the presence of a brain tumor and to determine its type and grade. These tests may include a biopsy, which involves removing a small piece of tissue from the brain for analysis, or a lumbar puncture, which involves taking a sample of cerebrospinal fluid from the spine.[20]

It's important to note that not all brain tumors cause symptoms, especially in the early stages. Therefore, routine screening for brain tumors is generally not recommended for people who are not at high risk, such as those without a family history of brain tumors or other risk factors. However, if you experience any persistent or unusual symptoms such as headaches, seizures, or changes in vision, you should talk to your doctor about the possibility of a brain tumor and undergo appropriate testing.

1. **Pre-processing:** pre-processing refers to the steps taken to prepare raw data for further analysis or modeling. Pre-processing is an important step because raw data may be incomplete, inconsistent, or contain errors that can impact the accuracy and reliability of the analysis or model[21]

Pre-processing techniques may include:

- **Data cleaning:** This involves identifying and correcting or removing any errors, inconsistencies, or missing values in the data.
- Data transformation: This involves converting data into a more suitable format for analysis or modeling. For example, this may involve scaling or normalizing data to ensure that it is on the same scale or range.
- **Feature selection:** This involves selecting the most relevant features or variables in the data to be used in the analysis or model.
- **Dimensionality reduction:** This involves reducing the number of features or variables in the data while still retaining as much relevant information as possible. This can help to reduce computational complexity and improve model performance.

- **Sampling:** This involves selecting a subset of the data to be used in the analysis or modeling. This can be particularly useful for large datasets or when the data is imbalanced.

2. **Skull Stripping:** Skull stripping, also known as brain extraction or brain masking, is a neuroimaging technique used to remove the skull from a three-dimensional image of the brain. This technique is commonly used in medical imaging, such as Magnetic Resonance Imaging (MRI), to isolate the brain and remove the surrounding tissue, such as the skull and scalp, from the image.[22]

The process of skull stripping involves segmenting the image into different regions, including the skull, brain tissue, and surrounding tissue. The skull is then removed from the image, leaving only the brain tissue. This process is important because it allows for more accurate analysis of the brain, such as measuring the volume of different brain regions or detecting abnormalities in brain tissue.[23]Skull stripping is typically performed using automated software algorithms, although it can also be done manually by a trained technician or radiologist. The accuracy of the technique can depend on several factors, such as the quality of the image and the algorithm used for segmentation. Skull stripping is an important step in many neuroimaging studies and can help researchers and doctors better understand the structure and function of the brain. It can also aid in the diagnosis and treatment of neurological disorders, such as brain tumors, stroke, and dementia.[24]

Segmentation: brain tumor segmentation is an important tool in the diagnosis, treatment, and monitoring of brain tumors. It allows clinicians and researchers to better understand the underlying biology of tumors and to develop more targeted and effective therapies.[25]

Brain tumor segmentation is a technique used to identify and separate the different regions of a brain image that contain a tumor. Segmentation is an important step in the analysis of brain tumor imaging data, as it allows researchers and clinicians to quantify and compare the size, location, and shape of tumors over time, and to monitor their response to treatment.

Brain tumor segmentation typically involves using advanced image processing algorithms to analyze MRI or CT scans of the brain.[26] The algorithms are designed to distinguish between different types of tissues in the brain, such as gray matter, white matter, and cerebrospinal fluid, as well as abnormal tissue that may indicate the presence of a tumor. There are several different approaches to brain tumor segmentation, including manual segmentation, semi-automated segmentation, and fully automated segmentation. Manual segmentation involves a trained expert manually outlining the tumor region on the images, while semi-automated segmentation involves a combination of manual and automated methods. Fully automated segmentation uses algorithms to automatically segment the images without any manual input. The choice of segmentation approach depends on the specific goals of the analysis,[27] as well as the expertise and resources available. While manual segmentation is generally considered the gold standard, it is time-consuming and subject to inter-observer variability. Semi-automated and fully automated methods can be faster and more consistent, but may be less accurate in certain cases.[28]

Feature Extraction: Feature extraction is typically done using advanced image processing techniques and machine learning algorithms. The process involves analyzing the medical images of the brain and identifying regions of interest that may contain a tumor. These regions are then segmented to isolate the tumor from the surrounding tissue.

Brain tumor feature extraction plays a crucial role in medical image analysis, helping to improve the accuracy and efficiency of brain tumor diagnosis and treatment. Brain tumor feature extraction is a process used in medical image analysis to identify and extract important features or characteristics from medical images of the brain that can help in the diagnosis and treatment of brain tumors. These features can include the size, shape, location, and texture of the tumor, as well as its growth rate, blood supply, and response to treatment.[29]

Post-processing: Post-processing in the context of brain tumor refers to the analysis and manipulation of medical images of the brain, such as Magnetic Resonance Imaging (MRI) or Computed Tomography (CT) scans, after they have been acquired. The purpose of post-processing is to enhance the quality of the images, improve the accuracy of the diagnosis, and assist in treatment planning. Post-processing techniques can be used to segment or isolate the tumor from the surrounding brain tissue, measure its size and shape, and assess its relationship to nearby structures. This information is essential for determining the type and grade of the tumor, which can guide treatment decisions.[30] post-processing techniques can provide valuable information for the diagnosis and treatment of brain tumors, helping doctors to make more informed decisions and improve patient outcomes.

Brain scans can be done through different methods, the most common of which is MRI scans. The proposed algorithms discussed in this paper make the use of MRI scans, and involve the discussion of three broad tumor types:

1. Benign Tumor: A benign tumor is a type of tumor that does not spread to other parts of the body or invade nearby tissue. Unlike malignant tumors, which are cancerous and can be life-threatening, benign tumors are usually not

harmful and do not pose a significant health risk. However, they can still cause problems if they grow large enough to compress nearby structures or interfere with normal organ function.
Benign tumors can develop in almost any part of the body, including the brain. In the case of brain tumors, a benign tumor can still cause symptoms such as headaches, seizures, or changes in vision or hearing if it grows large enough to press against the brain or affect its function.The diagnosis of a benign brain tumor is usually made through imaging tests such as MRI or CT scans. Treatment options for benign brain tumors may include surgery to remove the tumor, radiation therapy, or observation and monitoring over time.[31]

2. Pre-malignant Tumor: It is not necessary that benign tumors turn cancerous, they might not. However, they can turn cancerous if the uncontrolled multiplication of tumor cells continue. Such types of tumors need to be carefully monitored for changes in the cell such as the cell appearance and growth rate.[31]

3. Malignant Tumor: A pre-malignant tumor, also known as a pre-cancerous tumor, is a type of abnormal growth of cells that has the potential to develop into a cancerous tumor. These tumors are not yet cancerous, but they may progress to cancer over time if left untreated. Pre-malignant tumors can occur in various parts of the body, including the brain. In the brain, pre-malignant tumors are relatively rare compared to malignant brain tumors, but they do occur. The most common pre-malignant brain tumor is called a meningioma, which arises from the meninges, the protective membranes that

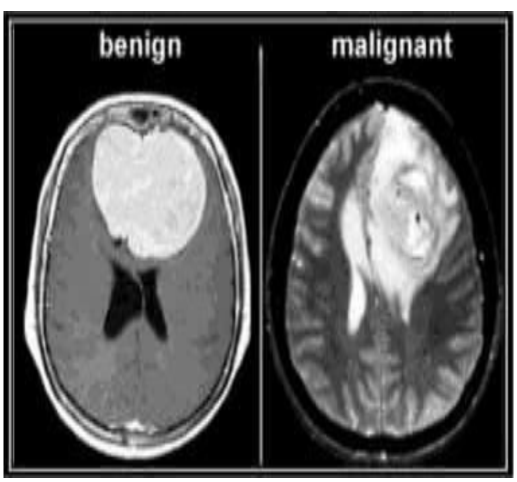

Fig2. Benign Tumor vs Malignant Tumor

surround the brain and spinal cord. Meningiomas are usually slow-growing and may not cause symptoms for many years. However, if left untreated, they can grow and compress nearby brain tissue, causing symptoms such as headaches, seizures, and vision problems. In some cases, meningiomas can become cancerous and spread to other parts of the body. The treatment for pre-malignant brain tumors depends on several factors, including the location and size of the tumor, the rate of growth, and the presence of symptoms.[31,32] In some cases, watchful waiting and regular monitoring may be sufficient. In other cases, surgery may be necessary to remove the tumor, especially if it is causing symptoms or is at high risk of becoming cancerous.

IMAGE SEGMENTATION

In recent years, deep learning-based approaches have emerged as the state-of-the-art in image segmentation. CNNs have shown remarkable success in detecting and segmenting brain tumors from MRI scans. Deep learning-based approaches have the advantage of being able to automatically learn and extract features from the images,[34,35] eliminating the need for manual feature engineering. However, deep learning-based approaches require large amounts of labeled data and computational resources, which can be a limitation in some applications.

Thresholding: Thresholding is a simple and commonly used technique for image segmentation. It involves setting a threshold value and classifying pixels in the image as either foreground or background based on their intensity values. [34]This technique is useful for segmenting images with clear contrast between foreground and background.

Region growing: Region growing is an iterative process of grouping together pixels that meet certain criteria, such as similarity in intensity or color. This technique is useful for segmenting objects with a relatively uniform appearance.

Edge detection: Edge detection involves identifying the boundaries between objects in the image. This technique is useful for segmenting objects with well-defined edges, such as organs or bones.[35]

Clustering: Clustering algorithms group pixels into clusters based on their similarity in terms of intensity, color, texture, or other features. This technique is useful for segmenting complex images with multiple objects and regions.

Watershed segmentation: The watershed algorithm is a region-based approach that segments an image based on the local minima and maxima of the image. This technique is useful for segmenting objects with irregular shapes and sizes.[36]

Deep learning-based segmentation: Deep learning-based segmentation involves training neural networks to learn how to segment images based on a training dataset. This technique has shown promising results in various medical imaging applications, such as tumor segmentation.[37]

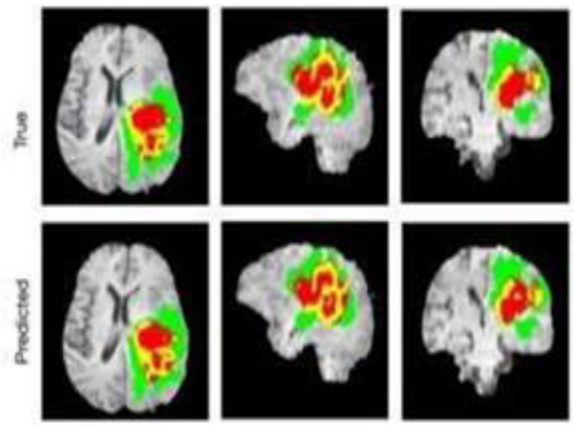

Fig.3. Fully Automatic Brain Tumor Segmentation

MAGNETIC RESONANCE IMAGING

Magnetic Resonance Imaging is a medical imaging technique in which radio waves generated by a computer and strong magnetic fields are used to provide detailed data and images of different parts and structures of the body.[38] Unlike CT scans, MRI does not make use of damaging radiation of X-rays and is of no harm to the human brain.[39] It helps in providing a cross-sectional image of the brain, which can be evaluated to ascertain the location and size of the tumor, if present. It is a non-invasive procedure. MRI machines are typically tube-shaped and surrounded by circular magnets. The patient is asked to lie on a table, which slides into the tube-shaped machine and examination is done. Normally, the water molecules in the body are arranged in a random manner. The working principle of MRI is that the magnetic field aligns the protons in the hydrogen atoms. These atoms are then exposed to a beam of radio waves, causing the protons to spin in a particular direction and emit faint signals which are received by the MRI machine. These signals are processed to form MRI images for further analysis.[40] Through this process, cross- sectional images of the brain can be created. These images can be used to locate the tumor and analyse its shape and size, and assess the best course of action to treat the brain tumor.

VI CONCLUSION

The paper discusses the use of various machine learning techniques, including fuzzy K-means clustering, random forests, and CNN architectures, for brain tumor detection and segmentation. The study compares and highlights some of the key points of state-of-the-art approaches used in this domain.The use of MKSVM algorithm by S. Krishnakumar et al. achieved the highest accuracy of 99.7% on the MMRI dataset. Similarly, a combination of feature extraction algorithm and CNN resulted in a high classification accuracy of 99.12%.One of the challenges faced by researchers in this domain is the lack of large publicly available datasets for training deep learning models. Furthermore, there is a need for structured labeling reports from experts such as neurologists and radiologists to aid future research.Class imbalance is another common issue encountered in brain tumor detection and segmentation. Researchers use data augmentation techniques such as rotating or scaling down existing images to address this issue. However, the anatomical location of the tumor region is often not known to the network, which can be a limitation.

Future research in this domain could focus on incorporating information about the tumor region's anatomical location in the neural network. However, the high resolution and large size of brain tumor images make training on such images challenging due to memory and computational power constraints.

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