Deep learning-based brain tumor detection: an MRI segmentation approach

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Abstract. The detection and segmentation of brain tumors from magnetic resonance imaging (MRI) scans are crucial for diagnosing, planning treatments, and monitoring patients with neurological disorders. This abstract provides a comprehensive overview of deep learning-based methods for detecting brain tumors, focusing on techniques for segmenting MRI images. Deep learning models, particularly convolutional neural networks (CNNs), have achieved impressive results in accurately segmenting brain tumors by learning distinctive features directly from the image data. Various CNN architectures, such as U-Net, DeepMedic, and 3D convolutional networks, have been specifically designed to address the challenges of brain tumor segmentation, including tumor heterogeneity, irregular shapes, and varying sizes. Additionally, the integration of multi-modal MRI data, such as T1-weighted, T2-weighted, and FLAIR images, has enhanced the robustness and accuracy of deep learning models for brain tumor detection. This abstract discusses the significant advancements, challenges, and future directions in deep learning-based brain tumor detection, emphasizing the potential of MRI segmentation techniques to support clinicians in early diagnosis and personalized treatment planning for patients with brain tumors.

Keywords: Brain Tumor, CNN, Deep Learning, MRI segmentation.

1 Introduction

MRI is a non-invasive technique that produces detailed 3-dimensional anatomical images of scanned objects. Its primary applications include identifying abnormalities, diagnosing conditions, providing treatment, and monitoring progress. MRI utilizes magnetism, radio...
waves, and digital computing technology to generate images of different body parts. The device depicted in Figure 1.2 is specifically designed for MRI and features a movable bed within a tubular structure surrounded by circularly arranged magnets. To undergo an MRI scan, the patient lies on the bed and passes through the magnetic chamber. Inside the chamber, the patient is exposed to a strong magnetic field, which causes the protons in hydrogen atoms to align. Radio waves are then directed towards the body, causing the protons to emit signals that can be detected by the MRI scanner [7].

To detect small changes and body structures, a computer processes the received information and generates a high-resolution image that allows effective visualization. In the field of biomedicine, MRI scans are commonly employed to visualize tiny organs and tissues with great detail. This technique enables users to analyze tissue differences and is considered superior to other medical imaging modalities. Previously, radiologists had to manually examine MRI images to detect brain tumors, a time-consuming and labor-intensive task [8]. Consequently, there is a need for an assistive tool that can facilitate accurate and early detection of brain tumors from MRI images. However, achieving early detection and precise classification of tumors in medical image processing is a challenging endeavor. A robust image segmentation process is necessary for this purpose. The segmentation process involves accurately separating the tumor region from the brain image, preserving its correct shape, size, and boundary. Although image segmentation is a critical step in tumor detection, achieving high accuracy is not an easy task. Therefore, it is crucial to perform accurate segmentation of the magnetic resonance image for further diagnosis.

MRI-based scanning offers several advantages for patients. Firstly, it does not involve the use of radiation or different ions, making it a safer option for individuals in lower and higher age groups who may be more vulnerable to the harmful effects of radiation. Additionally, MRI provides a higher level of imaging evaluation, particularly for soft tissues in the human brain, allowing for more detailed identification of various disorders at the tissue level. The scanning process is conducted in an imaging plane, minimizing the need for the patient to move on the MRI scanning bed. Furthermore, MRI scans can generate images of almost any part of the body from multiple angles, providing clear visualization of soft tissues. This technique is also relatively low-risk, as it has minimal potential for allergic reactions and is painless. Additionally, MRI can be used to monitor blood flow in the blood vessels, facilitating the identification of inflammation and swelling in the area under examination [9].

During the MRI scanning procedure, there are several challenges that need to be addressed. One such challenge is the noise generated by patient movement inside the MRI chamber, which is unavoidable particularly when dealing with tumors in the human mouth. Additionally, patients must endure exposure to a high static magnetic field, measured in units of tesla, during the scanning process. This exposure can lead to symptoms such as headaches, dizziness, nausea, and vomiting [9].
various levels of learning. This technique is referred to as deep learning because it utilizes existing deep neural networks, which can be categorized as unsupervised or supervised based on the learning process [10]. The hidden layers, which are positioned between the input and output layers, are responsible for the majority of the processing.

Brain tumor is a significant concern for individuals of all ages. It involves the abnormal growth of cells in the brain, resulting in swelling and changes in brain function. Medical image analysis plays a crucial role in the non-invasive treatment and clinical study of brain tumors. Doctors rely on analyzing MRI scans to identify the specific characteristics of the tumor. MRI scans are a non-invasive medical test that provides valuable information for doctors to plan and administer treatment. Early detection and diagnosis of tumors are essential for saving lives. However, MRI scans can be affected by noise, leading to inaccurate detection. Therefore, there is a need for the development of restoration and segmentation algorithms to improve the accuracy of tumor detection. Numerous researchers have developed algorithms for detecting brain tumors in MRI scans, but it remains a challenging problem. This thesis focuses on the development of restoration and segmentation algorithms for the detection and classification of brain tumors.

In recent years, there has been significant progress and advancement in the field of medical imaging and medicine. Various technologies have emerged to support surgical planning, diagnosis, and treatment of diseases. One widely accepted method for investigating brain tumors and treating brain-related diseases is through the use of brain MRI. However, a major challenge in this field is improving the quality of MRI images. Existing research studies often focus on analyzing error-free medical images from datasets, which may not be applicable when dealing with real-time medical images that are prone to noise and illumination artifacts. The visual quality of MRI images plays a crucial role in accurately detecting brain tumors. Therefore, it is essential to develop effective mechanisms to accurately trace and diagnose tumors among various analysis methods.

There are several widely accepted techniques for image segmentation, but none of them provide accurate and robust results. The field of image segmentation in brain MRI remains a challenging area in medical image processing. It is important to maintain a maximum number of discrete features in order to achieve high accuracy scores. However, this is currently not feasible with the current platform and classification process. Most optimization techniques have overlooked improvements in the decision-making process. This paper aims to address this issue by considering and implementing the neglected decision-making process in the algorithm. The proposed technique aims to comprehensively optimize and develop a globally accepted segmentation method and classification techniques for analyzing and detecting brain tumors from MRI scans. The main goal of this research is to develop a robust, efficient, and optimized tumor detection technique. The objective is to perform image segmentation, classification, and tumor detection from brain MRI scans. The primary objectives of this research are outlined below.

• The aim of this study is to conduct a literature review on the current methodologies used to accurately locate tumors in MRI scans.
• This review will also identify any gaps in the existing research. Additionally, we aim to find an efficient and cost-effective preprocessing method for noise removal.

• Furthermore, we will analyze and propose a precise tumor segmentation method using deep learning techniques for brain MRI scans.

• Lastly, we intend to develop a deep learning algorithm-based classifier to detect the type of tumor in brain MRI images.

2 Related Work

The presence of a psychological disorder in individuals can have various impacts, including the development of a brain tumor and the occurrence of panic attacks. Therefore, it is crucial to promptly and accurately identify brain tumors in order to initiate appropriate medical treatment. Image processing techniques, specifically those used in medical image processing, can aid in the improved diagnosis of tumors and other related diseases. The identification and classification of tumors with associated disorders require extensive knowledge and experience in the field of medicine. Consequently, there is a demand for a novel intelligent system that can detect and classify brain tumors. This study focuses on the classification of brain tumors into three hierarchical categories: pituitary, glioma, and meningioma, utilizing a deep learning approach. Accurately diagnosing and classifying tumors is essential for effective and efficient treatment. Convolutional Neural Networks (CNNs) can be employed in medical image processing to achieve the desired results. The CNN techniques involve training the data and segmenting the type of tumor into two distinct categories. The proposed classification technique is referred to as HDL2BT (Hierarchical Deep Learning-Based Brain Tumor) [11].

In this suggested study, the tumors are classified into four categories: meningioma, no-tumor, glioma, and pituitary. The proposed framework outperforms other techniques in identifying and segmenting brain tumors, achieving a precision of 92.13% and an error rate of 7.87%. This approach provides valuable assistance to patients in the medical field.

Brain tumors are considered to be a highly severe form of cancer that can affect individuals of all age groups. Among adults, some of the most commonly found tumors include pituitary, glioma, and meningioma cancer. This research work aims to propose and evaluate various techniques for diagnosing and categorizing brain tumors, with the goal of enhancing therapy facilities and improving clinical outcomes. In this study, a brain tumor classifier based on structured deep learning is suggested, utilizing convolutional neural networks (CNN). The input consists of four different classes: meningioma, no-tumor, glioma, and pituitary. The proposed model surpasses conventional techniques in segmenting and detecting brain tumors, achieving a 7.87% improvement in MR and an accuracy of 92.13%. Upon identifying the presence of cancer, the system further classifies the tumor into different categories. This suggested scheme presents a valuable contribution to medical assistance in the field of medicine [12].
The excessive growth of brain cells leads to brain disorders, which in turn affect the structure of the brain and ultimately result in brain cancer. When using a Computer-Aided Diagnosis system for accurate diagnoses in MRI images, several significant problems arise. This system aims to identify different diseases, such as glioma, meningioma, and pituitary tumors. In this work, a new Deep Convolutional Neural Network (DCNN) model is proposed for efficient identification of these diseases. Additionally, a three-step preprocessing technique is introduced to enhance the quality of MRI images. The design incorporates batch normalization for rapid development, including a deep learning rate and a simple setup of layer weights. The suggested design includes only a few convolutional and max-pooling layers, as well as training sessions, making it computationally efficient. A comparative study of the proposed architecture with other models is presented. When evaluated on a dataset of 3394 MRI images, the proposed model achieves an exceptional competitive accuracy of 98.22%, with 99%, 99.13%, 97.3%, and 97.14% accuracy in recognizing glioma, meningioma, pituitary, and normal images, respectively. Experimental findings demonstrate the reliability of the proposed architecture, which improves the speed and efficiency of identifying various brain illnesses.

A deep convolutional neural network model has been proposed for the diagnosis of brain disorders, including gliomas, meningiomas, and pituitary tumors. The model aims to achieve high classification accuracy and rapid results. To accomplish this, a suitable brain tumor dataset is selected for training and testing. A three-step preprocessing technique is applied to the MRI images to remove unwanted features, denoise the images, and enhance their resolution. The images are then characterized based on their attributes using a framework. The proposed technique is evaluated using 394 MRI images from the dataset, resulting in an overall precision of 97.72% and accuracy rates of 99% for glioma, 98.26% for meningioma, 95.95% for pituitary tumors, and 97.14% for normal images. The suggested model can serve as an accurate automated computer-aided detector for critical brain disorders in real-world applications involving MRI images [13].

Brain tumors are ranked 19th among all types of cancers and 10th among severe tumors. In Mexico, the incidence rate of cancer is 3.5 per 100,000 people, making it the second and fifth leading cause of death in the age groups of 0-18 and 18-29, respectively. Early clinical diagnosis plays a crucial role in determining the patient's chances of survival. For example, a tumor with a lethality score of four can double in size within 25 days, significantly reducing the patient's life expectancy [2]. Nuclear Magnetic Resonance (NMR) is a non-radioactive and non-intrusive technique used for producing high-resolution images of the human body's internal structures. It is one of the methods employed for tumor detection. Although MRI allows visualization of the brain region affected by the tumor, its effectiveness is limited by the inaccessible nature of some tissues. In this study, four NMR image classification algorithms were developed, each with varying levels of effectiveness and potential for improvement. Among these algorithms, the Support Vector Machine demonstrated superior performance. However, further research is required to accurately compare the performance of different algorithms. An effective algorithm was designed for image preprocessing in conjunction with classification algorithms. Future research can explore the use of larger image datasets or higher resolution images for algorithm training. The findings and...
Brain tumors affect both adults and children and are characterized by the uncontrolled growth of brain cells within the skull. Due to their diverse nature, cancer cells are difficult to characterize. Convolutional neural networks (CNNs) are a popular machine learning approach for brain tumor recognition and visual learning. In this study, a dense EfficientNet based on CNN with min-max normalization was proposed to categorize 3260 T1-weighted contrast-enhanced brain magnetic resonance images into glioma, meningioma, pituitary, and no tumor groups. The proposed network, which includes complex and dropout layers, aims to improve the distinction of cancer cells by combining data augmentation with min-max normalization. The dense CNN method accurately classifies images in a small database, making it an efficient technique. The research findings show that the proposed framework achieves a training accuracy of 99.97% and a testing accuracy of 98.78%. The recently developed EfficientNet CNN architecture is a valuable tool for decision-making in brain tumor diagnostic tests due to its high precision and positive F1 score. Compared to other studies using the same dataset, this study achieved a classification accuracy of 98.78% using dense EfficientNet with min-max normalization. The proposed method outperforms other deep learning techniques in terms of precision accuracy and F1 score, making it a significant predictive tool for brain tumor detection. Glioma has the lowest detection performance with an F1 score of 98%, while pituitary has the highest detection rate of 100%. Dense CNN outperforms other deep learning techniques in terms of performance and classification accuracy, enabling quick localization and identification of tumors. Furthermore, by reconfiguring several layers for medical image segmentation, a better preprocessing approach can be employed for rapid recognition of critical medical imaging disorders using fuzzy thresholding ideas or nature-based algorithms. The main objective of the proposed design is to reduce the number of factors and processing time without compromising performance [15]. An adaption technique is required since the model that was developed using old data is changed every time new data is added because of the change in the data [20].

This research proposes a differential deep CNN architecture for the classification of MR brain images. The performance of the model is evaluated based on various metrics such as precision, loss values, sensitivity, accuracy, F1-score, precision, and specificity. The experimental analysis using the differential deep CNN model demonstrates improved results, achieving an accuracy rate of 99.25%, sensitivity of 95.89%, specificity of 93.75%, precision of 97.22%, and F1-score of 95.23%. The model also exhibits a low loss ranging from 0.1 to 0.2. Comparatively, the suggested differential deep CNN model outperforms other approaches in classifying brain tumors.

An extensive collection of medical images is crucial for optimizing deep learning algorithms. The acquisition of this database was carried out by a dedicated team through TUCMD, resulting in improved effectiveness of the proposed approach. Additionally, the design of the differential deep-Convolution NN utilized a database that underwent evaluation, assessment, and analysis by qualified medical experts. The research findings indicated that the
Differentiation of brain tumors using TUCMD data aligned with the diagnoses made by doctors. This demonstrates the importance of deep learning in the field of medical science and highlights its potential for future medical applications.

In this study, a novel automatic model for brain tumor segmentation and classification using a Deep CNN is introduced. The key difference between this work and previous studies is the utilization of multiple processing pathways at three different spatial scales, inspired by the functioning of the human visual system. Unlike existing approaches, this neural model does not require any pre-processing steps to remove the skull or vertebral column from the input images. It can effectively analyze MRI scans from various perspectives (sagittal, coronal, and axial) and identify meningioma, glioma, and pituitary tumors. The proposed technique is evaluated on a dataset of 3064 MRI image scans from 233 patients, and its performance is compared to conventional machine learning and deep learning methods. Remarkably, the suggested approach achieves a tumor classification accuracy of 97.3%, surpassing the performance of other techniques using the same dataset [19].

This work presents a fully automatic technique for segmenting and classifying brain tumors using a CNN with a multiscale processing architecture. The system's performance is evaluated using a dataset of T1-weighted MRI images, including publicly accessible ones. Elastic data transformation is used to augment the training dataset and reduce overfitting. The achieved performance parameters are among the top 10 techniques according to the BRATS 2013 standard. The experimental results are compared with seven other brain tumor classification techniques that also use the same dataset. The proposed system achieves a classification accuracy rate of 97.3% and successfully segments and categorizes meningioma, glioma, and pituitary tumors using a multiscale CNN with three processing paths. The proposed approach demonstrates excellent segmentation performance, with an average Dice index, sensitivity, and precision of 0.828, 0.940, and 0.967, respectively. However, due to the variability of the three tumor types, false positives can occur in some images, including areas of the skull and vertebral column that are not excluded. The proposed classification and segmentation method can help address additional medical imaging challenges and assist doctors in diagnosing brain cancers.

Future research will involve designing an FCN architecture to classify the same dataset of MRI images and evaluating its performance in comparison to the proposed techniques [20].

The literature survey examines and analyzes the significant advancements in brain tumor image classification research. Each paper's summary, results, and accuracy are provided. Various techniques are used to classify Brain MRI, and the best classification methodology is chosen for classifying the brain images. The survey offers valuable insights into the selection of classification methods and highlights potential considerations for future approaches. Chapter 3 focuses on the framework and enhancement of brain tumor classification based on MRI datasets, building upon the discussions in Chapters 1 and 2, which provide an overview of the research and a review of the relevant literature, respectively. Notably, the importance of preprocessing for noise removal in MRI and the development of efficient segmentation techniques using deep learning are emphasized.
3 Methodology

Image processing often involves the task of image enhancement, which aims to improve the quality of an image. One important aspect of image enhancement is contrast, which refers to the range of brightness values present in the image. Contrast is particularly significant in distinguishing objects from their background, as it deals with various visual properties. Contrast enhancement processes are employed to make objects more distinguishable, stand out, or appear clearer. These processes involve manipulating the brightness and color differences between objects in the image. Various algorithms are available for contrast enhancement, which facilitate the interpretation and analysis of images. One commonly used approach is the piecewise linear function, which aims to increase the range of gray levels in the image being processed [5, 6]. This is an enhancement based on intensity and its general form is as given in eq.(1)

\[ I_o(x, y) = f(I(x, y)) \]  

Where \( I(x, y) \), \( I_o(x, y) \) are input and output images and \( f \) is a transformation function.

Median filtering is a widely used technique for non-linear filtering. It is particularly effective in removing salt and pepper noise from images. The filter operates based on two intrinsic properties: efficient attenuation of impulsive noise and preservation of image edges. While similar to mean filtering, the median filter is considered superior to both mean filtering and linear filtering. Median filters are commonly employed to reduce noise in images before performing higher-level processing tasks. In this study, the median filter was chosen due to its ability to produce clear and smooth results, although it does reduce image sharpness. Other advanced image filtering techniques, such as unsharp masking, rank order processing, and morphological processing, are also available. The median filter works by replacing each pixel value with the median value of its neighboring pixels. The term “window,” “mask,” or “kernel” is used to describe the pattern of neighboring pixels. These neighbors are moved across the entire image, one pixel at a time. The median value is calculated by converting and sorting all the pixel values within the window. Each pixel is then replaced with the middle or median value of the pixel values. This process is performed to replace all the pixel values in the entire image [88]. This technique helps to smooth or enhance the image.

The wavelet transform consists of two main steps: filtering and sub-sampling, which are used to compute the image. The sub-sampling can be performed at different levels of decomposition, and at each level, a 3-dimensional image is obtained. These detailed images contain high-frequency information in the horizontal, vertical, and diagonal directions. Breaking down the images in this way allows for the perfect reconstruction of the original image without any damage. In practice, there are various types of wavelet transforms available, and one of the improved versions of the Discrete Wavelet Transform (DWT) is the Stationary Wavelet Transform (SWT).
The classical Discrete Wavelet Transform (DWT) has a limitation caused by down sampling, leading to a loss of information as depicted in Figure 1. To overcome this drawback, the Stationary Wavelet Transform (SWT) was developed to restore translation invariance [89]. Unlike the DWT, the SWT does not involve down sampling between levels, resulting in improved time-frequency localization. The process of both SWT and DWT is illustrated in Figure 2. The wavelet decomposition exhibits sharp transitions in the images, enabling accurate denoising. The stationary wavelet transform offers properties and qualities that enhance the effectiveness of image denoising, and various techniques such as Daubechies, Haar, Coiflets, Symlet, Biorthogonal, and Orthogonal wavelets can be employed [90]. In this study, the Daubechies wavelet is utilized.

Fig. 1. DWT decomposition process

Fig. 2. SWT decomposition process

The field of mathematical morphology [94, 95] investigates the structural characteristics of objects and their relationships to extract image components. Morphological operators are non-linear and require two sets of input data. The first set is the binary image, while the second set is the structural element, also known as a mask. The structural element can take various shapes, such as square, diamond, disk, etc., and is applied to the binary image. The value of each pixel is then calculated based on the sliding mask over the binary image. The two fundamental operations in morphological operators are dilation and erosion [6, 7]. The dilation function increases the original size of the objects in every image whereas the erosion will reduce the size of each object. The mask act as a key role in achieving desired results. Generally, the shape and the size of mask are selected arbitrarily; hence, the mask that is selected shall be in appropriate shape and size for different diagnostic purposes. Disk-shaped mask is more commonly used on medical images [9].

This section describes the methodology of region growing based brain tumor segmentation (BTS) using MRI images. The methodology consists of three phases: preprocessing, region growing segmentation, and tumor extraction. The brain image cannot be directly used for region growing segmentation and needs to undergo preprocessing steps to prepare it for segmentation. The input is an MRI brain image of the tumor region obtained from medical imaging. The segmentation process in the proposed system involves preprocessing steps.
such as contrast enhancement, median filtering, and SWT technique. In addition to segmentation, region extraction is performed as a morphological operation to automatically extract the segmented regions. The overall process flow diagram of the denoising based seeded region growing technique is shown in Figure 3 below.

**Fig. 3.** Tumor extraction using segmentation method

Image enhancement refers to improving the visual quality of an image by reducing the ambiguity between similar areas or by emphasizing certain features such as edges, lines, or textures. The process of image enhancement involves both pre-processing and enhancing the image.

**Fig. 4.** Brain image enhancement

### 4 Results and Discussion

This section presents the results obtained from the experiments conducted on BTS, a brain tumor extraction system. The system is compared with other competitive enhancement and segmentation methods. The implementation of the proposed system is done in PYTHON (Python 9.3). The experiments were performed using real-time MRI brain images. The dataset used for the experimentation consisted of MRI brain slices that explicitly contained the tumor, along with the corresponding ground truth image.
The image data used in this study were sourced from the Kaggle database. The dataset comprises brain MRI images that are categorized into normal, melanoma, and benign images. In total, there are 2562 images available. All of these images were in JPEG format and had a resolution of 512x512 pixels. Kaggle is widely recognized as an open-source database that is frequently utilized by researchers.

Fig. 5. Brain image sample data

Fig. 6. Input with tumor region and frequency of grey level

Fig. 7. Contrast image input and frequency distribution of grey levels

The outcomes of this study are presented, and the segmentation result and extracted tumor region are displayed in Figure 6. Figure 7 shows the brain images utilized in this research. Figure 8 illustrates the original brain image and the frequency distribution of gray levels. The graph displays how the pixels are distributed in the image based on their gray levels. The majority of pixels in the image have low intensity, resulting in a high intensity range between 0 and 50. The second peak in the gray level occurs between 60 and 120. Some pixels in the skull area have a gray level above 250, indicating a change in frequency of occurrence. The figures demonstrate that the contrasts differ from the original image, with the frequency of image pixels being close to zero. Contrast enhancement could potentially sharpen the object.
boundaries, and to achieve this, a median filter is employed to smooth the image pixels. Figure 8 shows the median filtered image and the corresponding frequency distribution of gray levels.

Fig. 8. Median filtered image

The image with enhanced contrast is processed using the median filtering technique, which is known for its ability to smooth the pixels and remove salt and pepper noise while preserving the edges. However, this technique may also introduce false edges in the objects. To address this issue, the median filtering technique is used in contrast enhancement to suppress these false edges and prevent the extraction of undesired objects. The results of applying both the median and SWT filters are depicted in Figure 4.15. The SWT filter is employed to reduce abrupt frequency level changes in the image without downsampling or loss of information. After enhancement, the gray level frequency ranges from 150 to 200, making the results beneficial for object extraction from the image.

Fig. 9. Median and SWT filtered image

The seeded region growing technique is used to test MRI brain data set images, and the results are presented in Table 1. These values are then compared with the corresponding ground truth images. To assess the similarity of the tumor region results, Jaccard and Dice similarity coefficients, as well as Jaccard distance metrics, are employed. The Jaccard coefficients indicate a high degree of similarity, as they are close to 1. This is also true for all the values in the table. Notably, image 6 exhibits the highest value, indicating the highest level of similarity. Furthermore, the dice similarity coefficient is also close to 1, suggesting that all the images possess a high degree of similarity.

The Jaccard distance value should be close to 0, indicating minimal error. According to Table 1, image 6 has the lowest error rate due to the segmentation method used. All images, except image 3, show a low error rate. These results provide evidence that the seeded region.
5 Conclusion

The deep learning methods based on MRI segmentation have made significant progress in the field of medical imaging and neurology for brain tumor detection. By employing convolutional neural networks (CNNs) and other deep learning architectures, researchers have achieved impressive results in accurately identifying and segmenting brain tumors from MRI scans. The literature review demonstrates that deep learning models, particularly CNNs, can effectively learn complex patterns and features directly from raw MRI data, enabling precise segmentation of tumors despite their varied shapes, sizes, and heterogeneity. Different CNN architectures, such as U-Net, DeepMedic, and 3D convolutional networks, have been customized to address the specific challenges encountered in brain tumor segmentation, showing promising outcomes across various datasets and imaging techniques.
References