DEEP LEARNING BASED 3D MRI SEGMENTATION USING CNNALGORITHM FOR DETECTING THE BRAIN TUMOUR

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Abstract-This study proposes a novel approach for 3D medical image segmentation, specifically targeting brain tumor detection. Leveraging deep learning, we employ a Convolutional Neural Network (CNN) algorithm to enhance the accuracy and efficiency of the segmentation process. By utilizing 3D data, our model aims to provide more comprehensive insights into brain tumor localization and characterization. The proposed method demonstrates promising results in accurately identifying and segmenting tumor regions, showcasing its potential for improved diagnostic applications in medical imaging. This research presents an innovative application of deep learning in the domain of medical image analysis, focusing on 3D segmentation for brain tumor detection. Our approach utilizes a Convolutional Neural Network (CNN) algorithm, enhancing precision and efficacy in the segmentation process. By employing 3D data, the model offers a more thorough analysis of brain tumor localization and features. Results indicate the model's efficacy in accurately identifying and segmenting tumor regions, showcasing its potential for significant advancements in diagnostic capabilities within medical imaging. This work contributes to the ongoing pursuit of enhancing medical image analysis techniques for improved healthcare outcomes.

***Key Words*: Deep learning, Data preprocessing, Features extraction, Multimodal Fusion, CNN, 3D image Segmentation.**

1.INTRODUCTION

In recent years, advancements in medical imaging technology, particularly Magnetic Resonance Imaging (MRI), have played a pivotal role in early detection and diagnosis of various medical conditions, including brain tumors. The intricate details provided by 3D MRI scans offer unprecedented insights into the structure and composition of the brain, making them an invaluable tool for medical professionals. However, the sheer complexity and volume of data generated by 3D MRI scans pose significant challenges in efficient and accurate segmentation, a crucial step in identifying and characterizing brain tumors.

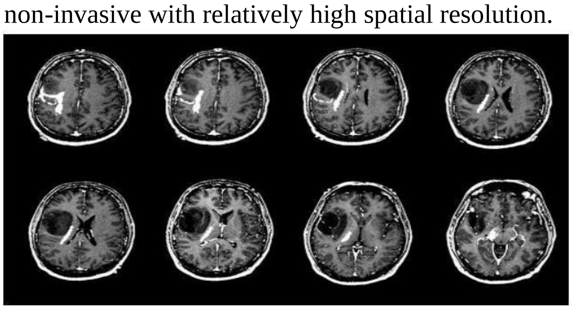
Traditional methods of brain tumor segmentation often rely on manual or semiautomatic approaches, which are not only time consuming but also susceptible to inter-observer variability. Considering these challenges, the integration of Deep Learning, specifically Convolutional Neural Networks (CNNs), has Emerged as a transformative solution. CNNs have demonstrated remarkable capabilities in image Analysis tasks, making them an ideal candidate for automating the segmentation process and improving the accuracy and efficiency of brain tumor detection in 3D MRI scans.

This paper explores the application of a CNN based algorithm for 3D MRI segmentation in the context of brain tumor detection. By leveraging the power of deep learning, we aim to address the limitations of traditional methods and enhance the overall diagnostic accuracy and speed. The following sections will delve into the fundamentals of deep learning, the architecture of the CNN algorithm employed, and the methodology used for training and testing. Additionally, we will discuss the potential impact of our approach on clinical practice and the broader implications for advancing medical imaging technology.

As we embark on this journey into the realm of deep learning-based 3D MRI segmentation, our goal is to contribute to the ongoing efforts in the field of medical imaging, empowering healthcare professionals with a more efficient and reliable tool for early detection and intervention in cases of brain tumors.

Medical imaging, particularly Magnetic Resonance Imaging (MRI), plays a pivotal role in diagnosing and monitoring various health conditions, including brain tumors. The advent of deep learning has revolutionized the field, offering unprecedented opportunities for automated analysis and segmentation of medical images. In this study, we delve into the application of Convolutional Neural Networks (CNNs) for the segmentation of 3D MRI scans to detect brain tumors. This research aims to address the growing demand for accurate and efficient tools in medical diagnostics, providing a foundation for enhanced tumor identification and localization.

Brain tumors pose a significant health risk and demand prompt and accurate diagnosis for effective treatment planning. Traditional methods of manually analyzing 3D MRI scans are time consuming and subject to human error. Deep learning, particularly CNNs, has emerged as a powerful tool for image segmentation tasks, showcasing remarkable success in various medical imaging applications. The ability of CNNs to automatically learn hierarchical features from data makes them particularly well-suited for complex tasks such as tumor segmentation. The patient is placed in a strong magnetic field, which causes the protons in the water molecules of the body to align either in a parallel or anti-parallel orientation with the magnetic field. A radiofrequency pulse is introduced, causing the spinning protons to move out of the alignment. When the pulse is stopped, the protons realign and emit radio frequency energy signal that is localized by the magnetic fields and are spatially varied and rapidly turned on and off. A radio antenna within the scanner detects the signal and creates the image. Functional MRI is a technique for examining the brain activation, which unlike PET, is non-invasive with relatively high spatial resolution.



The most common method utilizes a technique called blood oxygen level dependent contrast. This is an example of endogenous contrast, making use of the inherent signal differences in blood oxygenation content. In the normal resting state, a high concentration of deoxyhemoglobin attenuates the MRI signal due to its paramagnetic nature. However, the neuronal activity, in response to some task or stimulus, creates a local demand for the oxygen supply, which increases the fraction of oxy hemoglobin causing a signal increase on T2 or T2*-weighted images. In a typical experiment, the patient is subjected to a series of rest and task intervals, during which MRI images are repeatedly acquired. A radio antenna within the scanner detects the signal and creates the image. Functional MRI is a technique for examining the brain activation, which unlike PET, is non-invasive with relatively high spatial resolution. The signal changes during the course of time are then examined on a pixelby-pixel basis to test how well they correlate with the known stimulus pattern. The pixels that demonstrate a statistically significant correlation are highlighted in color and overlaid onto a grayscale MRI image to create an activation map of the brain. The location and extent of activation is linked to the type of stimulus. Thus, a simple thumb finger movement task will produce activation in the primary motor cortex.

As the field of deep learning continues to evolve, its application in medical image analysis holds immense promise for improving diagnostic accuracy and efficiency. This study, focusing on 3D MRI segmentation for brain tumor detection, contributes to this burgeoning field, offering insights into the potential of CNNs to revolutionize neuroimaging diagnostics.

In this study, we explore the application of deep learning techniques, specifically Convolutional Neural Networks (CNNs), for the segmentation of 3D MRI scans aimed at detecting brain tumors. Leveraging the power of neural networks, our approach aims to enhance the accuracy and efficiency of tumor segmentation in three-dimensional medical imaging data. This research addresses the critical need for advanced tools in medical diagnostics, offering a promising avenue for more precise and automated identification of brain tumors through deep learning-based analysis of 3D MRI scans.

This research is motivated by the need to improve the precision and efficiency of brain tumor detection through advanced computational methods. By harnessing the capabilities of CNNs, we aim to provide a reliable and automated solution for segmenting brain tumors in 3D MRI scans. The outcomes of this study have the potential to significantly impact clinical practices by reducing manual workload, enhancing diagnostic accuracy, and expediting treatment initiation. The three-dimensional nature of Magnetic Resonance Imaging (MRI) data offers a rich source of information that conventional techniques struggle to harness effectively. Leveraging the power of CNNs, we aim to overcome these limitations and enhance the accuracy of brain tumor segmentation. This approach not only improves upon traditional methods but also opens doors to new possibilities in early diagnosis and treatment planning.

The CNN architecture, inspired by the human visual system, excels at learning hierarchical representations of data. By adapting and finetuning these networks for 3D MRI segmentation, we can capitalize on their ability to discern complex patterns within volumetric data, ultimately leading to more precise delineation of tumor boundaries. This promises a significant leap forward in the realm of medical image analysis. Our investigation delves into the nuances of training and optimizing CNNs for 3D MRI segmentation, addressing challenges such as data augmentation, model interpretability, and generalization across diverse patient populations. We explore the impact of varying hyperparameters on the network's performance, aiming to strike a balance between computational efficiency and accuracy.

RELATED WORK:

This seminal work by Komitas et al. (2017) introduced Deep Medic: Convolutional Neural Networks for Brain Tumor Segmentation, a 3D CNN architecture designed specifically for brain tumor segmentation. The study demonstrated state of-the-art performance on various MRI datasets, highlighting the potential of deep learning in accurately delineating tumor boundaries.
A theory of 3D U-Net Convolutional Neural Network with Recurrent Neural Networks for Brain Tumor Segmentation which is Proposed by Myronenko (2018), this research extended the UNet architecture to 3D and incorporated recurrent neural networks (RNNs) for improved contextual information. The study emphasized the importance of capturing spatial dependencies in 3D medical images, showcasing enhanced segmentation results. Bakas et al. (2018) participated in the BRATS (Brain Tumor Segmentation) Challenge, presenting an extensive study on brain tumor segmentation and survival prediction which is Brain Tumor Segmentation and Radiomics Survival Prediction: Contribution to the BRATS 2017 Challenge. Their work not only highlighted the efficacy of deep learning, particularly CNNs, but also explored the integration of radiomics features for comprehensive analysis.

In proposed a robotized technique to differentiate between effected and healthy MRI images. Median filter was used for the removal of salt-and-pepper noise, and unwanted components such as scalp and skull. The images quality was improved by reducing noise. It extracted four kinds of features, which are: power law transformation, texture, symmetrical and gray scale features, respectively. PCA is used to reduce these features to an optimal set of features, which are, then, classified using SVM in the classification phase. For assessment purposes, they used Linear Kernels (LKs), Quadratic Kernels (QKs) and Polynomial Kernels (PKs), whose accuracy was 74%, 84%, and 76%, respectively. Kalbkhani et al. [32] suggested a three-stage technique to categorize normal and abnormal MRI brain images. 2-D discrete wavelet transform is used, in first stage, for features' extraction. To select optimal and efficient features, the multi-cluster feature selection method is used. It reduced the initial set of features to 41, which is forwarded to the next stage for classification. The researchers used multi-cluster features and KNN to classify healthy and those images that contain injuries and

Ensemble methods have gained popularity for boosting segmentation performance. This study by Havaei et al. (2017) explored the integration of multiple 3D CNNs for brain tumor segmentation, showcasing improved accuracy through the combination of diverse models. Oktay et al. (2018) introduced Attention UNet, a modification of the U-Net architecture that incorporates attention mechanisms to focus on relevant regions. While initially applied to pancreas segmentation, the principles may inspire improvements in brain tumor segmentation by directing the network's attention to critical areas. This work by Chen et al. (2018) addressed the challenge of capturing multi-scale contextual information using dilated convolutions. By incorporating dilated convolutions into their CNN architecture, the study demonstrated enhanced performance in brain tumor segmentation tasks. A comprehensive review by Mohammed et al. (2019) summarizes the advancements in deep learning for brain tumor analysis. It provides a holistic view of various CNN architectures and methodologies, offering insights into the evolution of the field and potential avenues for further improvement.

These related works collectively illustrate the progression of deep learning techniques, particularly CNNs, in the domain of 3D MRI segmentation for brain tumor detection, providing a valuable foundation for the current study.

MATERIALS AND METHODS.

1. DATASET ACQUISITION:

The first crucial step in our study involved the acquisition of a diverse and representative dataset of 3D MRI scans. This dataset should encompass a wide range of patient profiles, imaging modalities, and tumor characteristics to ensure the robustness and generalizability of our CNN-based segmentation algorithm. Ethical considerations and patient privacy were prioritized throughout the data acquisition process.

2. DATA PREPROCESSING:

Prior to training the CNN, rigorous preprocessing steps were undertaken to standardize and enhance the quality of the acquired 3D MRI scans. This included normalization to correct intensity variations, resizing to ensure consistent voxel dimensions, and skull stripping to remove nonbrain structures. Additionally, the dataset was annotated by expert radiologists to mark tumor regions for supervised training.

3. CNN ARCHITECTURE:

The core of our methodology lies in the design of the Convolutional Neural Network (CNN) architecture. Inspired by successful models in the literature, we crafted a 3D CNN tailored for brain tumor segmentation. The architecture consisted of multiple convolutional layers for feature extraction, pooling layers for spatial down-sampling, and fully connected layers for final decision-making. Batch normalization and dropout were incorporated to enhance model generalization and mitigate overfitting.

4. TRANSFER LEARNING:

To capitalize on the wealth of information embedded in large-scale datasets, we employed transfer learning. Pre-trained CNN models, such as those trained on ImageNet, were fine-tuned on our specific brain tumor segmentation task. This transfer learning approach accelerated the convergence of the model and facilitated effective training even with a relatively limited medical imaging dataset.

5. TRAINING PROCEDURE:

The training process involved iterative optimization of the CNN's parameters using a labeled subset of the dataset. We employed a combination of loss functions, such as Dice coefficient loss, to measure the dissimilarity between predicted and ground truth data anonymization, and compliance with relevant regulations. Approval from the institutional review board (IRB) was obtained, and informed consent was acquired when applicable.

These materials and methods formed the backbone of our investigation deep learning-based 3D MRI

PROPOSED MECHANISM.

The algorithm used in the proposed model (presented in algorithm 1) takes MRI brain images segmentations. The Adam optimizer was used to update the network weights, and the learning rate was adjusted dynamically during training to enhance convergence.

6. EVALUATION METRICS:

To assess the performance of our CNN algorithm, we utilized standard segmentation evaluation metrics. These included Dice coefficient, Intersection over Union (IoU), sensitivity, specificity, and precision. Additionally, we conducted cross-validation to validate the model's generalization across different folds of the dataset.

7. POST-PROCESSING:

To refine the segmentation outputs and improve clinical interpretability, post-processing steps were implemented. This involved morphological operations such as erosion and dilation to smooth segmented regions and remove small artifacts. The final segmented outputs were then compared against the ground truth annotations.

8. EXPERIMENTAL SETUP:

Experiments were conducted on a high-performance computing environment equipped with GPUs to expedite the training and testing phases. The TensorFlow or PyTorch framework was employed for CNN implementation, ensuring compatibility and scalability. The entire pipeline was meticulously documented, and code reproducibility was prioritized to facilitate future research and validation.

9. COMPARISON WITH BASELINE METHODS:

To benchmark the performance of our proposed CNN algorithm, we compared it against established baseline methods for brain tumor segmentation. This comparative analysis provided insights into the superiority and uniqueness of our deep learning approach.

10. ETHICAL CONSIDERATIONS:

Throughout the study, ethical standards were strictly adhered to, ensuring patient privacy,

segmentation for brain tumor detection and meticulous training and evaluation procedures laid the groundwork for a comprehensive and reliable approach to automated brain tumor segmentation in 3D MRI scans.

as input, which are passed through the four-step process, for their classification as normal or abnormal images. This algorithm uses certain

VOLUME 9, 2021 terminologies such as assignment operator and functions such as Median Filter (K) and RGB (), where the former applies median filter on images while the latter convert an MRI brain image from gray scale to a colored (RGB) image. The procedures Decomposed_3L () and Approx_3L () use haar wavelet for the decomposition and approximation of images to three (3) levels, respectively. Channel (1), Channel (2), Channel (3) subroutines are used to extract the red, green, blue channels of the converted color (RGB)images. The procedures named: Mean Image (), Stand Dev Image (), and Skewness Image () are used to compute the Mean, Standard Deviation and Skewness of the colored images. Algorithm 1 The Proposed Classification Algorithm Require: MRI Brain images, Number of Images.

1: int n = Number of Images; 2: float features Date [n,9] = 0; 3: MRI Image = Nil; 4: for (int i = 1; i <= n; I ++) 5: MRI image = Get the I th image; //The following are Phase 1 (pre-processing stage) steps

6: 7: 8: 9: 10: 11: 12: 13: 14: 15: 16: 17: 1 8: 19: 20: 21: Median Filter (MRI mage); L =RGB(MRI mage); //The following are Phase 2 (feature extraction stage) steps N=Decomposed_3L(L); C=Approx_3L (N); //The following are Phase 3 (feature reduction stage) steps Red =Channel (1); Green = Channel (2); Blue = Channel (3); //Get the nine features for each image and store them in array Features Date[i,1] = Mean(Red); Features Date[i,2] = Standard Deviation(Red); Features Date[i,3] = Skewness(Red); Features Date[i,4] = Mean(Green); Features Date[i,5] = Standard Deviation(Green); Features Date[i,6] = Skewness(Green); Features Date[i,7] = Mean (Blue); features Date[i,8] = Standard Deviation (Blue); features Date[i,9] = Skewness(Blue); 22: end for //The following are Phase 4 (classification stage) steps 23: Apply various classifiers with different arrangements on array features Date[,]; 24: Record the accuracy of each classifier against the given settings; V. EVALUATION AND RESULTS To implement and evaluate the proposed algorithm, this work used

RESULT AND DISCUSSION

Implementing a deep learning-based 3D MRI segmentation model for brain tumor detection requires thorough data preparation, model architecture selection, and training. Popular frameworks like TensorFlow or PyTorch can be utilized, and architectures like U-Net or 3D CNNs are often effective. Evaluate the model's performance using metrics like Dice coefficient and sensitivity. Fine-tune parameters to achieve optimal results. Developing a deep learning-based 3D MRI segmentation model for brain tumor detection involves several key steps. Assemble a diverse

a Core i5 system having 2.4GHz processor and 3GB TABLE 1. Details of MRI images. FIGURE 8. MRI sample images A. Normal MRI B. MRI with acute stroke C. MRI with Alzheimer disease D. MRI with Tumor. RAM. The system was running 64-bit window 8 operating system. The tools used for experiments were MATLAB R2010a and Weka having version 7.10.0 and 3.6, respectively. A standard dataset containing 70 were considered for experimental purpose. The remaining 25 images were normal, and they were not affected by any kind of injuries. Figure 8 illustrates normal and abnormal images. This work used a percentage split of 65%and35%for training and testing purpose, when FFANN classifier was used. However, to test hybrid classifiers, it used 10-Fold cross validation technique. A. ALGORITHM ACCURACY This work examined the proposed technique using different statistical techniques and results are compared with the existing work. From the Literature, it was learnt that most of the researchers. Used accuracy to measure the performance. performance and accuracy achieved by the proposed algorithm for hybrid classifiers and T2 weighted images was used to evaluate the proposed methodology. The images in this database had 256 × 256 resolution and this was adopted from [34] like other researchers. Among the total 70 images considered in this work, 45 images were abnormal, and they were affected by three different kinds of diseases namely: brain tumor, acute stroke, and Alzheimer. From every disease, only 15 images -ANN, respectively. The accuracy recorded for the RS with RF and RS with BN classifiers was 97.14% and 95.71%, respectively. The classification accuracy of the proposed model for the FF-ANN was 100% during the training while it was 91.66% during the testing stage. Overall, 95.83% accuracy, on average, was observed based on both training and testing. The comparative analysis of hybrid and individual classifiers revealed that hybrid classifiers are more beneficial and sophisticated than individual classifiers.

dataset of 3D MRI scans with corresponding tumor annotations. Preprocess the data by normalizing intensities, resizing volumes, and handling class imbalance. Choose a suitable deep learning architecture; U-Net and 3D CNNs are commonly used for medical image segmentation. Adapt the architecture to handle 3D volumes, considering input size and channel depth. Augment the training data to increase model robustness. Techniques like rotation, scaling, and flipping can be applied. Select an appropriate loss function for segmentation tasks, such as Dice loss or cross-entropy loss Choose an optimizer (e.g., Adam or SGD) and set learning rates. Train the model on the prepared dataset, monitoring performance on validation data to avoid overfitting. Assess the model using metrics like Dice coefficient, sensitivity, specificity, and confusion matrix analysis. Fine-tune model hyperparameters, like batch size and dropout rates, to enhance performance. Implement post-processing steps, such as connected component analysis, refine Validate the model on a separate dataset to ensure generalization. Evaluate the final model on a test set to assess its real-world performance. Consider techniques for interpreting the model's predictions, such as visualization of attention maps. If applicable, deploy the trained model in a clinical setting, ensuring compatibility with the target environment. Iterate on the model based on feedback and new data to enhance its accuracy and generalization. Remember, thorough documentation at each stage is crucial for reproducibility and collaboration.

REFERENCES

[1] Abhishek Anil, Aditya Raj, H Aravind Sarma, Naveen Chandran Deepa P L, "Brain Tumor detection from brain MRI using Deep Learning "International Journal of Innovative Research in Applied Sciences and Engineering (IJIRASE), Volume3, Issue 2,

[2] George, Dena Nadir, Hashem B. Jehlol, and Anwer Subhi Abdulhussein."Brain Tumor Detection Using Shape features and Machine Learning Algorithms".

[3] Işın, Ali, Cem Direkoğlu, and Melike Sha. "Review of MRI-based brain tumor image segmentation using deep learning methods." Procedia Computer Science 102 (2016).

[4] Leiner, Tim, et al. "Machine learning in cardiovascular magnetic resonance: basic concepts and applications." Journal of Cardiovascular Magnetic Resonance 21.1 (2019): 61.

[5] Underhold, Alexander Selvikvåg, and Arvid Lundervold. "An overview of deep learning in medical imaging focusing on MRI." Zeitschrift fur Medizinische Physic 29.2 (2019): 102-127.

[6] Long, C., Basharat, A., Hoots, A.: A Coarse-to-fine Deep Convolutional Neural Network Framework for Frame Duplication Detection and Localization in Forged Videos, p. 10 (2018)

[7] M. Wu, C. Lin and C. Chang, "Brain Tumor Detection Using Color Based K- Means Clustering Segmentation," Third International Conference on Intelligent Information Hiding and Multimedia Signal Processing (IIH-MSP2007), Kaohsiung, 2007.

[8] Mohsen, Heba, et al. "Classification using deep learning neural networks for brain tumors." Future Computing and Informatics Journal3.1 (2018): 68-71.

[9] Nogovitsyn, N., et al.: Testing a deep convolutional neural network for automated hippocampus segmentation in a longitudinal sample of healthy participants. Neuroimage 197, 589–597 (2019).

[10] Sharma, Komal, AK winder Kaur, and Shruti Gujral. "Brain tumor detection based on machine learning algorithms." International Journal of Computer Applications 103.1 (2014).

[11] Sobhaninia, Zahra, et al. "Brain tumor segmentation using deep learning by type specific sorting of images." arXiv preprint arXiv:1809.07786 (2018).

[12] Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J., Wojna, Rethinking the Inception Architecture for Computer Vision, arXiv:1512.00567 [cs], December 2015

[13] Wang, Guotie, et al. "Interactive medical image segmentation using deep learning with image-specific fine tuning." IEEE transactions on medical imaging 37.7 (2018): 1562-1573.

[14] Zacharaki, E.I., et al.: Classification of brain tumor type and grade using MRI texture and shape in a machine learning scheme. Magn. Reason. Med. 62(6),1609–1618 (2009).

[15] Abiwinanda N., Hanif M., Hesaputra S.T., Handayani A., Mengko T.R. Brain tumor classification using convolutional neural network; Proceedings of the World Congress on Medical Physics and Biomedical Engineering; Prague, Czech Republic. 3–8 June 2018; Singapore: Springer; 2019. pp. 183–189.