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Deep learning applications in MRI for brain tumor detection and image segmentation

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Abstract. Deep learning holds great potential in the field of MRI applications. By leveraging its advanced algorithms and neural networks, it can effectively analyze and interpret intricate patterns in medical images, aiding in precise disease detection, segmentation, and classification. Integrating deep learning techniques with MRI technology is expected to revolutionize radiology practice, facilitating enhanced diagnostic accuracy and customized treatment strategies, ultimately leading to improved patient outcomes. This article provides an overview of of the latest advancements in deep learning techniques applied to magnetic resonance imaging, specifically focusing on brain tumor detection and segmentation. The study examines eight different deep learning methods, including a multi-scale convolutional neural network, U-Net-based fully convolutional networks, cascaded anisotropic convolutional neural networks, missing modality-based tumor segmentation, Hough-CNN for deep brain region segmentation, k-Space deep learning for accelerated MRI, Multi-level Kronecker Convolutional Neural Network, and a heuristic approach for clinical brain tumor segmentation. Each method is analyzed, highlighting its specific techniques, advantages, and limitations. The comparative performance of these methods in terms of accuracy and efficiency, addressing key factors such as computational requirements, training time, and robustness, was discussed in this article. By assessing the merits and limitations of different approaches, this review seeks to offer valuable perspectives on effective utilization of deep learning techniques in clinical MRI settings for detecting and delineating brain tumors.

Keywords: deep Learning, MRI, CNN.

1. Introduction

The automated detection and characterization of brain tumors in MRI images play a vital role in medical imaging. [1] Brain tumors are complex and heterogeneous, making accurate detection and segmentation challenging. However, recent advancements in deep learning techniques have significantly improved automated tumor recognition, segmentation accuracy, and efficiency. [2] Automated tumor detection and segmentation can aid in the early diagnosis of brain tumors. Medical professionals can initiate timely treatment plans and interventions by accurately identifying the presence and location of tumors. Early detection can significantly improve patient outcomes and increase survival rates. Automated segmentation of brain tumors also enables precise delineation of tumor boundaries. This information is vital for treatment planning, as it helps determine the extent of

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tumor growth and invasion. Accurate segmentation allows for targeted treatment strategies, such as radiation therapy or surgical resection, minimizing damage to healthy surrounding tissues.

Deep learning techniques have revolutionized the field of medical imaging, offering significant advancements in the analysis and understanding of images, particularly in the context of brain tumor evaluation and partitioning. The utilization of deep learning in automated tumor detection and segmentation has shown significant improvements in accuracy compared to traditional methods. Deep learning models can learn from vast datasets, capturing intricate tumor characteristics and enhancing their ability to differentiate between tumor and normal brain tissues. This increased accuracy leads to more reliable diagnostic results and enables tailored treatment plans for patients.

A comprehensive review of the latest progress in utilizing deep learning techniques to accurately detect brain tumors and segment MRI images. Specifically, I focus on eight state-of-the-art techniques, including a multi-scale convolutional neural network, U-Net-based fully convolutional networks, cascaded anisotropic convolutional neural networks, missing modality-based tumor segmentation, Hough-CNN for deep brain region segmentation, k-Space deep learning for accelerated MRI, Multi-level Kronecker Convolutional Neural Network, and a heuristic approach for clinical brain tumor segmentation.

By exploring these methods, this article aims to evaluate their efficacy, strengths, limitations, and comparative performance. Understanding the merits and drawbacks of these approaches will provide valuable insights into selecting the most suitable method for accurate brain tumor identification and segmentation in clinical practice.

Incorporating deep learning techniques into the MRI-based brain tumor data analysis is promising for enhancing diagnostic precision, treatment strategy development, and monitoring processes. By advancing our knowledge in this field, we can ultimately enhance patient outcomes and contribute to the progress of personalized medicine in neuro-oncology.

2. Analysis of 8 cases

Antonio Di Ieva and her team introduce an innovative heuristic method [3] that harnesses the power of deep learning to automate the process of tumor segmentation in clinical magnetic resonance imaging. Their approach incorporates convolutional neural networks (CNNs) and complementary techniques, optimizing the precision and effectiveness of tumor segmentation. The dataset's images were resized to 160×176×112 by excluding the infra-tentorial structure, specifically the cerebellum while preserving the entire supra-tentorial anatomy. Then, the pre-processed images are fed into a CNN model. The team introduced a heuristic approach by incorporating various processing steps to refine the initial segmentation obtained from the CNN. The algorithm's architecture is shown in Fig. 1.

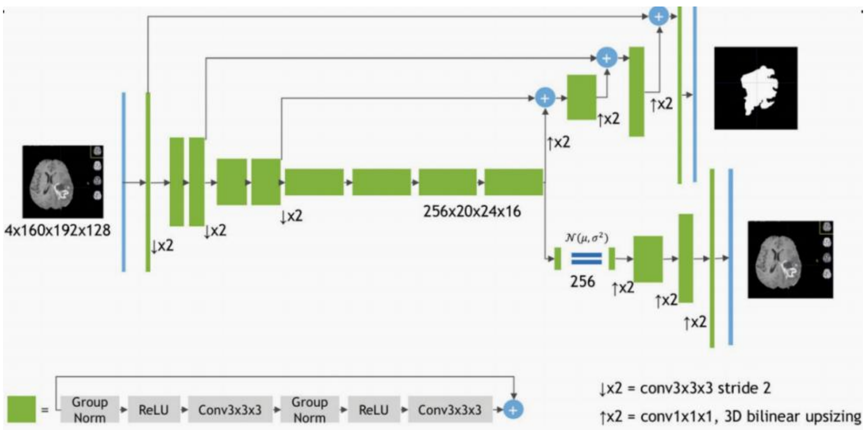

Figure 1. Schematic visualization of the convoluted neural network architecture [3].

This hybrid approach aims to overcome the limitations of CNN-based segmentation, such as false positives or incomplete tumor delineation. The team conducted experiments on a dataset of MRI scans from brain tumor patients to evaluate their method. They compared the performance of their heuristic approach with traditional image segmentation methods and pure CNN-based approaches. Multiple evaluation metrics, including sensitivity, specificity, and DSC, were employed to assess the accuracy of the segmentation results. The approach showed improved sensitivity, specificity, and DSC scores, indicating better tumor detection and segmentation accuracy. Antonio and her team suggest further research to explore the generalizability of the proposed method to different clinical scenarios and tumor types. They also highlight the potential for incorporating multi-modal imaging data, such as functional MRI, to enhance segmentation accuracy. The team believes that applying deep learning approaches in clinical settings can contribute to more accurate diagnoses, treatment planning, and monitoring for patients with brain tumors.

The method that Antonio Di Ieva and her team proposed has no missing modalities due to the BraTS training set used for the training set. Still, it is normal for modalities to be missing caused by variations in protocols and procedures across different hospitals. To address the modal incompleteness in MRI images, which can pose challenges for accurate tumor segmentation. Yan Shen and Mingxuan Gao proposed an approach [4] utilizing advanced computational techniques to accurately analyze brain tumor data. Their method employs cutting-edge convolutional neural networks, paving the way for improved outcomes in tumor analysis. This approach enables the model to handle cases where certain modalities are missing in the MRI data, enhancing its robustness in the presence of missing modalities. Firstly, they normalize the gray value to a range between -1 and 1 and employ a center window cropping technique to extract the MR image's central region for each input channel. Then, they set up a separate channel input modality for each modality because the basic model structure follows the U-net. So that the use of distinct feature maps on four separate channels allows for the encoding of abstract segmentation information that remains robust in the presence of channel loss, they generate higher-resolution segmentation outputs by progressively increasing the spatial dimensions through bottom-up upsampling. This process involves combining and integrating channel-separate feature maps at different levels to create the final segmentation results, decoding through three stages of consecutive blending and up-sampling, using convolutional operations to predict segmentation probabilities at different resolutions, and using bottleneck feature maps for structural layer segmentation. The final segmentation output is generated with the same resolution as the input MR image. The final results prove that their method can achieve relatively high accuracy despite missing modalities.

Guotai Wang and his team have developed an innovative approach [5] utilizing cascaded anisotropic convolutional neural networks (CNNs) to achieve automated segmentation of brain tumors in MRI scans with remarkable precision. This method effectively identifies and outlines tumor regions, providing accurate delineation for further analysis and diagnosis. They used pre-processed MRI images. The proposed MRI segmentation framework comprises three networks: WNet, TNet, and ENet. WNet focuses on segmenting the entire tumor, TNet focuses on segmenting the tumor core, and ENet aims to segment the enhancing tumor core. Anisotropic convolution and multi-scale prediction techniques are employed for efficient feature extraction and considering different scales. The networks incorporate residual connections to facilitate information flow and enhance training convergence.The proposed approach incorporates multi-view fusion by integrating the segmentation outcomes obtained from multiple orthogonal perspectives. The bounding boxes are computationally derived in the training phase using the ground truth data as a reference. In contrast, during testing phase, they are derived from the previous network's segmentation output. This cascaded framework enables sequential segmentation of distinct tumor substructures, taking into account contextual information, which contributes to achieving accurate and comprehensive tumor segmentation in MRI images. The model can improve computational efficiency while maintaining a certain level of accuracy, but it requires longer training and testing times.

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Francisco Javier Díaz-Pernas and his team [6] have proposed a CNN-based method for fully automated MRI image segmentation and classification. Their approach using a multi-scale convolutional neural network was inspired by the multi-scale processing mechanism observed in the human visual system. They utilized three processing pathways that operated at different spatial scales to emulate this. The team initially processed MRI images by examining each pixel using a CNN architecture. They employed a sliding window technique, where three convolutional paths with varying kernel sizes were used to extract features based on different scales. These scale-specific features were then combined through a single convolutional layer. To address the overfitting issue, a dropout layer was incorporated to enhance the robustness of the model.

Additionally, the final layer employed softmax activation to produce feature responses, contributing to the overall effectiveness of the approach. The final layer utilized softmax activation to generate feature responses. Elastic transformations were employed as a technique to enhance the dataset. These transformations introduce deformations and variations into the images, expanding the available training samples. By incorporating elastic transformations, the model becomes more robust and capable of handling diverse input scenarios. This technique significantly increased the number of training images in each iteration, effectively doubling the dataset's size. The experimental results showcased the model's effectiveness, as it achieved high sensitivity and accuracy. It obtained a DICE metric of 0.828. That shows a relatively low number of false positives and misses.

Moreover, the model exhibited exceptional accuracy in identifying tumors, achieving an impressive accuracy of 0.973, which is more accurate than many current models.The method proposed by Francisco Javier Díaz-Pernas and his team has a little bit higher computational complexity and excellent accuracy than the method proposed by Guotai Wang and his team. However, the evaluation approach employed by Francisco Javier Díaz-Pernas and his team in their study lacks the same level of thoroughness as the evaluation approach utilized by Guotai Wang and his team in their research.

Muhammad Junaid Ali and his team introduce a novel ML-KCNN method for accurately segmenting brain tumors in volumetric MRI data encompassing multiple imaging modalities.They found that the approach proposed by Francisco Javier Díaz-Pernas and his team has some problems in practice: building such an architecture requires expensive hardware, resulting in high costs. In practice, hospitals definitely prefer to build lightweight segmentation systems. Their proposed method solves this problem without increasing the runtime and computational complexity.Their proposed methodology leverages advanced deep learning techniques to enhance the segmentation of brain tumors in MRI scans. It involves a series of three key steps designed to optimize the accuracy and precision of the segmentation outcomes. Fig. 2 illustrates the architecture of the algorithm.

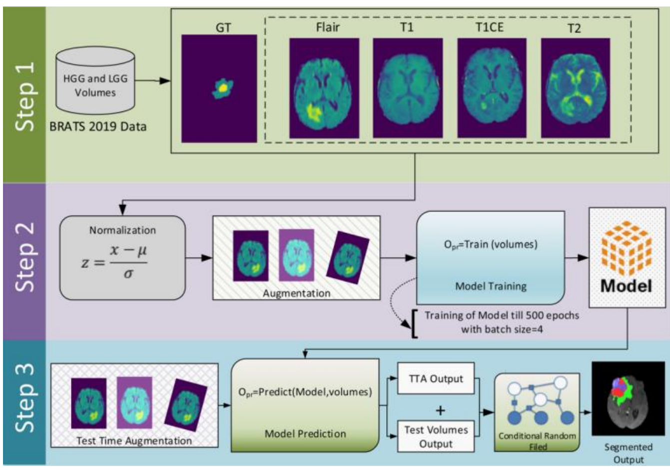

Figure 2. System model of the proposed methodology. [7]

The algorithm begins by addressing intensity variations in brain MRI scans through Z-score normalization to mitigate imaging variances. Mean and standard deviation are calculated within specific regions, considering tumor areas during training and the entire volume during validation. To enhance tumor identification and segmentation, the team introduces the ML-KCNN architecture, a modified version of the U-Net model commonly used in medical imaging. The ML-KCNN architecture incorporates the MLKC block, which captures critical information using different filter sizes at multiple levels, significantly expanding the receptive field without increasing complexity. This approach effectively captures intricate tumor structures and hierarchical information by segmenting tumors into multiple components and integrating contextual details. Instead of Conv3D Transpose, the network utilizes Upsample 3D blocks for upsampling, reducing parameter count while maintaining computational efficiency and segmentation quality. Additionally, a post-processing technique combining Conditional Random Fields (CRF) and Connected Component Analysis (CCA) is applied to smooth boundaries and reduce false positives in the model's predictions. These improvements lead to higher DSC scores, indicating better overlap between predicted and ground truth glioma regions and improved sensitivity and specificity for tumor detection.

Dong Hao and his team developed an automated method [8] for brain tumor analysis utilizing a U-Net based fully convolutional network. This method enables accurate and efficient evaluation of brain tumors, aiding in the understanding and diagnosis of these conditions. Firstly, They used elastic deformation to process the data expansion to obtain enough variable training data. Then, the U-Net model is applied to perform pixel-level classification for tumor detection and segmentation. The U-Net architecture comprises an encoding path for down-sampling and a decoding path for up-sampling. To ensure consistent output dimensions throughout the network, zero-padding was utilized. This approach effectively preserves the spatial information during both the down-sampling and up-sampling processes, maintaining the integrity of the feature maps at each network stage. This ensured that the spatial dimensions of the feature maps remained consistent throughout the network. Dong Hao and his team conduct experiments using publicly available brain tumor datasets to evaluate the performance. They utilized the adaptive moment estimator (Adam) as their parameter estimation technique to train the neural network. Their study provides a model with better efficiency and higher accuracy and proposes a more comprehensive data enhancement scheme.

However, The method proposed by Dong Hao and his team uses a 2-dimensional network because it is a fully-connected layer CNNs, which is limited by GPU memory constraints; if a 3-dimensional network is used, then the accuracy can be even higher. Yoseo Han and his team have introduced a novel method [9]. This approach aims to efficiently reconstruct the incomplete k-space data, improving the quality and accuracy of the overall image reconstruction process. This method has low GPU memory requirements compared to fully-connected layer CNNs, enabling accurate reconstruction through a simple Fourier transform of the interpolated data. In addition, the researchers exploit the relationship between the structured low-rank properties of k-space and the sparsity observed in the image domain. By leveraging deep convolutional minor frames, their model can handle a wide range of k-space sampling patterns, extending beyond traditional Cartesian trajectories. Furthermore, it achieves calibration-free k-space interpolation with multiple channels, thereby enhancing its versatility and broad applicability. The team propose training neural networks in two steps: the learning phase, where basis functions are selected based on a sparsity prior, and the inference phase, where the interpolated signal is estimated using the learned filters. They emphasize the importance of ReLU nonlinearity for adaptation and generalization. The paper also explores extending their approach to parallel imaging with multiple receiver coils. They suggest converting the image signal into a sparse representation using residual learning and incorporating shift-invariant transforms to improve performance. They present strategies for handling different sampling trajectories, such as extra regridding layers for non-Cartesian trajectories and zero-filling for Cartesian trajectories.Finally, the experimental results can prove that the image reconstruction quality of the team's proposed method is still relatively excellent.The team provides a relatively good solution to the problem of MRI image analysis, where the use of fully-connected layer CNNs leads to high GPU memory requirements and consequently low efficiency.

Fausto Milletari and team propose a segmentation framework for volumetric clinical images [10]. It utilizes Hough voting, patch-wise back-projection, and CNN architectures to accurately segment anatomical regions. The framework applies to various modalities, including MRI, focusing on deep brain structures. Accurate segmentation is achieved using a Hough voting strategy. CNNs consist of layers that apply convolution operations to analyze input data and activation functions to introduce non-linearities. These layers help the model learn and extract useful features from the data through a process called back-propagation during training. They use PReLU activation functions and employ dropout to prevent overfitting. Max-pooling layers are used sparingly to maintain localization accuracy. The traditional approach of patch-wise classification is sub-optimal due to the lack of statistical priors. The team proposes a segmentation method based on simultaneous anatomy localization and robust contour extraction to overcome this. They use a Hough voting strategy with CNNs to localize the anatomy and retrieve the contour.

The CNN classifies patches and extracts features from its intermediate layers. These features are used in the voting strategy. During training, patches are collected from both foreground and background and the CNN is trained to differentiate them. The resulting network parameters define the CNN. Then, a database is created using a dataset of patches and their corresponding features and votes. During testing, the CNN is employed to categorize voxels within an unseen volume based on their characteristics, and the K-nearest neighbour search is performed to retrieve similar patches from the database. These patches' votes and segmentation patches contribute to the final segmentation. The approach can be extended to multiple regions by creating region-specific databases. The whole volume is processed at once using modified network structures to improve efficiency. This model gets better accuracy in segmenting large and high contrast regions, but relatively small and low contrast regions are harder to segment and less accurate. Hough-CNN have been introduced to target deep brain regions specifically, allowing for more precise tumor segmentation.

3. Conclusion

A comprehensive overview of the current applications of deep learning in MRI for brain tumor classification and segmentation has been provided in this article. I have discussed eight different methods that have been developed, each addressing specific challenges and utilizing unique approaches.

Different automated brain tumor segmentation methods have their own strengths and limitations, making them suitable for specific scenarios. Researchers can choose the most appropriate method based on the characteristics and requirements of the given application. Integrating Dong Hao et al.'s method and Yoseo Han et al.'s method presents an opportunity to leverage the advantages of both approaches. Combining Dong Hao's U-Net-based fully convolutional network in three dimensions with Yoseo Han's low GPU memory method for interpolating missing k-space data makes it possible to overcome the memory limitations typically associated with 3D networks. This integrated approach can potentially yield higher accuracy in brain tumor segmentation. Furthermore, certain methods, such as those proposed by Antonio Di Ieva et al. and Yan Shen et al., complement each other by addressing different aspects of the problem. Antonio Di Ieva's heuristic approach, which combines CNNs with additional image processing techniques, focuses on refining initial segmentations. In contrast, Yan Shen's method tackles modal incompleteness in MRI images. When combined, these methods provide a more comprehensive solution, accounting for scenarios not considered by either method alone. By strategically combining and complementing these existing approaches, researchers can advance the automated brain tumor segmentation field, improving its effectiveness, robustness, and applicability in clinical practice.

Overall, these deep learning methods have significantly advanced the field of MRI-based brain tumor segmentation. Each method has its strengths and weaknesses, with considerations such as accuracy, computational resources, and specific challenges in mind. With further refinement and development, these techniques can enhance patient care, facilitate early detection, and improve treatment outcomes in neuro-oncology.

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