Brain Tumor Detection in Medical Image Using Deep Learning

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Abstract- Brain Tumor passes significant health risks due to their high mortality rates and challenges in easy diagnosis. Advances in medical imaging, particularly MRI, combined with artificial intelligence (AI) have revolutionized tumor detection, segmentation and classification. This study presents a comparative convolutional neural network (CNN) modulus of brain tumor detection on MRI medical images. Brain tumors are among the deadliest forms of cancer, requiring accurate and timely diagnosis to improve patient survival rates. Magnetic Resonance Imaging (MRI) plays a pivotal role in detecting brain abnormalities. In recent years, deep learning (DL) techniques, particularly Convolutional Neural Networks (CNNs), have significantly enhanced the automatic detection and classification of brain tumors in medical images. This paper presents a comprehensive approach to brain tumor detection using deep learning, evaluating model performance on publicly available datasets. The study also discusses the challenges and future prospects in applying deep learning for real-world clinical use.

Keywords-Brain Tumor Detection, Deep Learning, Medical Imaging, MRI, Convolutional Neural Networks, Segmentation, Classification.

INTRODUCTION

Deep learning and artificial intelligence have made considerable strides recently, especially in medical picture processing. New techniques that make it simpler and faster for doctors to diagnose diseases have been developed because of this. To avoid life-threatening diseases and disorders, the biomedical area needs accurate and effective information, which can only be provided by computer-assisted technology. The lack of annotated data is one of the key obstacles to accelerating the development of deep-learning in clinical or medical applications. Recent developments in deep learning algorithms, however, have demonstrated that larger datasets produce greater prediction performance and higher accuracy. A dangerous and unpredictably developing kind of cancer in a brain known as a brain tumor can seriously harm the brain. New techniques for identifying brain tumors from medical photos have been developed thanks to recent developments in deep learning. This represents a significant advance since it may enable earlier recognition and management of brain cancers, potentially improving patient outcomes. In our research, we have developed a revolutionary deep learning method for identifying brain cancers/tumors. Our approach is based on a convolutional neural network-CNN called the U-Net design architecture, which was created especially for segmenting medical images. We trained our model on a dataset of brain MRI scans from BraTS'2020 and tested it on a batch of unseen images, Anatomical predictions made by our model have been 99.13% accurate. Here are some additional details about brain-tumors:

• Benign and malignant brain-tumors are the two main varieties. Benign tumors do not spread to other parts of the body and have no cancerous symptoms. Malignant 1 A. N. Author, B. N. Author and C. N. Author cancerous tumors have the capacity to spread to other organs.

• A brain tumor may occur anywhere in the brain. The three most typical types of brain tumors are meningiomas, gliomas and pituitary tumors.

• The size and location of the tumor can affect the symptoms of a brain tumor. Headaches, nausea, vomiting, seizures, and visual issues are a few of the typical symptoms.

• Brain tumors are often diagnosed with a combination of MRI, CT scan, and biopsy.

• Based on the size, kind, and location of a brain tumor different courses of treatment applied are Chemotherapy, radiation therapy, and surgery. Brain tumors are a serious condition, but early diagnosis and treatment can improve patient outcomes. Deep learning methods like the one we have developed have the potential to help doctors diagnose brain tumors earlier and more accurately, which could lead to better patient outcomes.

LITERATURE REVIEW

Several studies have explored DL models for brain tumor detection. Menze et al. introduced the BRATS challenge dataset, providing benchmark segmentation tasks for gliomas. Isensee et al. developed the nnU-Net framework, achieving state-of-the-art tumor segmentation without manual tuning.

Rajaraman et al. applied transfer learning on pretrained models like VGG16 and ResNet50 for brain tumor classification, showing promising results with limited training data. Other studies utilized hybrid models combining CNNs with Recurrent Neural Networks (RNNs) or transformers for enhanced feature representation.

Despite these advances, challenges such as small dataset sizes, variations in imaging modalities, and lack of interpretability hinder the clinical deployment of such models.

METHODOLOGY

SEGMENTATION IN MEDICAL IMAGING

Medical images from multiple modalities, including CT, MRI, and US, frequently display intricate structures and ambiguous features due to factors such as acquisition constraints, pathological conditions, and individual biological differences, which hinder accurate image analysis and diagnosis [4]. Image segmentation divides an image into sections based on homogeneous attributes such as color, brightness, texture, and responsiveness. Generally, segmentation facilitates the description of anatomical structures in an image by identifying regions of interest [4]. Traditionally, medical image segmentation was performed manually, slice by slice, requiring a high level of expertise to accurately define boundaries for individual areas. This manual editing process is time-consuming. Several segmentation techniques employing computer algorithms have been developed to manipulate and process digital images, enabling the analysis of 2D or 3D images. These techniques allow the visualization of human organs, soft tissues, and diseases, as well as image extraction, three dimensional reconstruction, and segmentation. By discerning similarities or differences between regions, images are divided into segments, enabling the quantitative or qualitative analysis of lesions and other areas of interest. This approach substantially enhances the reliability and accuracy of medical diagnoses. Computer-aided segmentation techniques can be categorized into three groups: supervised, interactive (semi-supervised), and automatic (unsupervised) [3], [11]. Supervised segmentation techniques utilize manually labeled training data for the detection of specific objects in images, which limits their scope [3]. Interactive segmentation techniques in medical imaging refine algorithms with user guidance, a process critical for diagnostics and interventions. Users actively define and adjust segmentations, improving accuracy, handling complex structures, and providing essential support for surgical planning and navigation [13]. Unsupervised (automatic) segmentation techniques split images into components without prior knowledge or user interaction. These methods are typically applied to segment well-circumscribed objects. Using stacks of medical images, they can generate roughly segmented images that can be further refined by human experts [12].

A. Steps in Medical Image Segmentation The steps involved in medical image segmentation include the following:

1. Data Collection: Create a medical imaging dataset divided into training, validation, and test sets. These include: a. Training Set: Used for model training. b. Validation Set: Used for hyperparameter adjustment. c. Test Set: Used for final model evaluation.
2. Image Preprocessing: Standardize input images, apply random rotation and scaling, and increase the dataset size for machine learning-based processing.
3. Medical Image Segmentation: Use appropriate segmentation techniques to process medical images and produce segmented outputs.
4. Performance Evaluation: Create performance indicators and assess the effectiveness of the segmentation techniques. Deep learning techniques have recently achieved significant advancements in image segmentation, surpassing the accuracy of traditional approaches. However, non-deep learning computational approaches, such as the Cellular Automata (CA) algorithm, have also shown promise for brain tumor segmentation using MR images [24]. The CA algorithm supports researchers and clinicians in radiosurgery planning and therapy assessment by differentiating necrotic and enhanced tumor tissue content. The CA algorithm involves three stages:

1. Volume of Interest (VOI) Selection: Over the tumorÃ¢ÂÂs largest visible diameter, background and foreground seeds are selected based on user-defined lines.
2. Strength Map Generation: Probability and level-set surface maps are obtained by running the CA algorithm on the VOI to impose spatial smoothness.
3. Final Segmentation: The necrotic tumor regions are segmented using the chosen enhanced and necrotic seeds. An automated framework was also developed in [24] for brain tumor segmentation. It identifies edema and necrosis components, as well as brain internal structures, using 3D MRI images. This deformable framework is constrained by spatial relations using fuzzy classification and symmetry based histogram analysis. The computational approach is applicable to various MRI modalities and tumor classes.

Fully convolutional networks
(FCNs) represent a pioneering deep learning model, successfully applying convolutional neural networks to semantic image segmentation. While traditional segmentation techniques, such as threshold-based, edge-detection-based, and region-based methods, are no longer as effective compared to deep learning-based methods, their underlying concepts remain valuable. These approaches leverage mathematical and digital image processing principles. Although they offer simplicity and high segmentation speed, they often lack accuracy and detail in complex cases.

DEEP LEARNING OVERVIEW

Deep learning represents a prominent perspective within the expanding fields of artificial intelligence (AI) and machine learning (ML). Using deep neural networks (DNNs), it mimics the cognitive learning mechanisms of the human brain, extracting features from extensive datasets, including text, images, and sound, often through an unsupervised approach [8]. Neural networks (NNs) comprise interconnected neurons that act as small information processors. Together, these neurons form a complete deep neural network capable of processing images end-to-end. As the number of hidden layers' increases, the network transitions into deep learning. Tackling the challenges of training deep networks requires effective layer initialization and batching techniques, positioning deep learning at the forefront of current research [3]. In computer vision, deep learning is applied in various areas such as pattern recognition, handwritten number recognition, and data dimensionality reduction. It is also utilized in processes like image segmentation, image recognition, scene analysis, image repair, and object tracking, demonstrating remarkable effectiveness in these domains [5].

A. Convolutional Neural Network (CNN)

CNNs are structured with layers dedicated to functions such as convolution, pooling, and loss calculation. The initial layer connects directly to the input image, featuring neurons corresponding to the pixel count. Intermediate layers receive inputs from the preceding layer. Convolutional layers extract features by convolving filters with input data, where kernels (filters) are designer-defined. Each neuron responds to a specific area of the input, known as the receptive field. Convolutional layers produce activation maps that depict the filter's impact on the input. Activation layers then introduce non-linearity post-convolution. Depending on the design, the next layer may be a pooling layer, which employs strategies like max pooling or average pooling to reduce output dimensionality. Fully connected layers extract high-level abstractions. During training, neural connections and kernels continuously optimize through backpropagation [14]. Within these layers, units have local connections, receiving weighted inputs from small neighboring units (the receptive field) in the preceding layer. As layers stack to create multi resolution pyramids, higher-level layers acquire features from progressively broader receptive fields [1]. CNNs share weights among receptive fields within a layer, reducing the number of parameters compared to fully connected neural networks. This weight-sharing mechanism provides CNNs with a significant computational advantage. Some of the most well-known CNN architectures include ResNet, AlexNet, DenseNet, U-Net, MobileNet, and GoogLeNet. This review study focuses on evaluating deep learning algorithms for MRI brain tumor image segmentation. However, deep learning also finds applications in other domains, such as agriculture. For instance, a review in [28] examined the use of deep learning approaches for detecting and classifying tomato plant diseases using plant images. Several DL architectures, including AlexNet, SqueezeNet, VGG, VGG16, ResNet, Faster R-CNN, LeNet, S-CNN, and MobileNet, were analyzed and reported. The performance of a deep learning algorithm (CNN) was compared with two machine learning algorithms, Support Vector

Classifier (SVC) and Random Forest (RF), for buccal X-ray image segmentation in [26]. Using threshold and region-based strategies, the study discovered and analyzed teeth structures and patterns with the help of decision support systems. Interestingly, the SVC and RF algorithms outperformed the CNN after a comprehensive comparison using the same data. This suggests that external factors may influence the application of DL approaches.

B. Recurrent Neural Networks (RNNs)

RNNs are specialized artificial neural networks designed for sequential data processing, such as time series and language. Unlike conventional feedforward networks, RNNs feature cyclical connections that form loops, allowing them to retain memories of past inputs. This cyclic structure enables RNNs to adeptly capture temporal dependencies, making them ideal for tasks involving sequences, such as language prediction and time series forecasting. In RNNs, the network's hidden layers retain information about previous inputs, enabling consideration of context from earlier sequence elements [16]. A feedback loop is employed, where the output of one cell serves as the input for the next time step, facilitating the learning of dependencies. RNNs are widely applied in time series analysis, natural language processing, and speech recognition. However, they face challenges such as vanishing gradients, which hinder the capture of long-range dependencies. To address these limitations, advanced architectures such as Gated Recurrent Units (GRUs) and Long Short-Term Memory (LSTM) networks have been developed, significantly improving the performance and reliability of RNNs in sequential data tasks [3].

DEEP LEARNING APPLICATION TO BRAIN TUMOR IMAGE SEGMENTATION

Numerous studies have employed deep learning techniques for segmenting brain tumor images. Essential studies have been selected, analyzed, and discussed below based on specific search criteria. The segmentation performance of these techniques is evaluated using a metric called the Dice score, which measures the similarity between predicted and ground truth regions. This determines the regions of interest (ROIs) to be automatically segmented. The key ROIs segmented in this review are the Tumor Core (TC), Whole Tumor (WT), and Enhanced Tumor (ET). A novel architecture called the 3D multimodal fully convolutional network (FCN) was proposed in [17] for segmenting brain MR images with isointense phases. The dataset comprised MR images of 11 healthy infants, including T1, T2, and diffusion-weighted (DW) sequences. The T2 and fractional anisotropy (FA) images were aligned with the corresponding T1 images and upscaled to a resolution of 1Ã1Ã1âmm31 \times 1 \times 1 \, \text{mm}^31Ã1Ã1mm3. Initial segmentations were generated using the iBEAT software, followed by manual editing to correct errors. The 3D FCN integrated coarse and dense layer information, refining segmentation performance by fusing features from different scales and incorporating contextual semantic information. This approach enabled accurate segmentation of multimodal brain MRI images. The study in [18] addressed the vanishing gradient problem in CNN and FCN models by introducing the ResNet model. This innovation incorporates "connection links" that facilitate the backward propagation of gradients, preserving spatial information and reducing computational time. The improved ResNet model, implemented in TensorFlow using the BraTS 2020 dataset, outperformed CNN and FCN models with higher accuracy and reduced computational time. ResNetâs shortcut connections enable efficient tumor detection without expert intervention, alleviating complexity and time constraints. The AGSE-VNet model for 3D MRI image segmentation was presented in [19]. Within the VNet architecture, a squeeze-and-excite (SE) module was integrated into the encoder, while an attention guide (AG) filter was included in the decoder. The encoder enhanced relevant features while suppressing irrelevant details, and the attention block removed background noise while guiding feature extraction (e.g., edges). Additionally, a categorical Dice loss function was employed to address class imbalance. The model was evaluated on the BraTS 2020 validation set, producing Dice scores of 0.69 for TC, 0.85 for WT, and 0.68 for ET. Although these results are promising, particularly for WT and TC, further improvements may be necessary to fully harness the modelâs potential. Study [20] employed an encoder-decoder CNN architecture for brain tumor segmentation using 3D MRI scans. The architecture featured an asymmetric design with a larger encoder and smaller decoder, along with an integrated auto encoder branch for regularization. To enhance feature clustering, particularly with limited training data, the architecture utilized a variational auto-encoder strategy. An ensemble of ten models was trained, yielding Dice scores of 0.884 for WT, 0.815 for TC, and 0.766 for ET on the BraTS 2018 test set. Additionally, the deepSCAN architecture and its variants demonstrated comparable performance, achieving Dice scores of 0.890, 0.830, and 0.810 for WT, TC, and ET, respectively, on the BraTS 2019 test set after incorporating lightweight local attention and instance normalization. BU-Net, an enhancement of the U-Net architecture, was introduced in [21]. It incorporates wide context modules and residual extended skip connections. The wide context block facilitates the transition from the encoder to the decoder by connecting the deconvolution layer output with the corresponding residual extended skip block output. Although the use of 2D convolution in BU-Net enhances contextual information acquisition and global feature aggregation, it results in a loss of context and local information across multiple image slices. To address class imbalance, a combined weighted cross-entropy and Dice loss function was employed. Evaluation on the BraTS 2017 and BraTS 2018 datasets demonstrated that BU-Net outperformed baseline methods, such as U-Net, EnsembleNet, Seg-Net, ResU-Net, PSPNet, S3DU-Net, NovelNet, TTA, and MCC, using the same optimizers and loss functions. However, further investigation is required to assess its performance under diverse algorithmic settings.

DISCUSSION

The studies reviewed demonstrate the effectiveness of various deep learning models in accurately segmenting brain MRI images, as evidenced by the reported Dice scores. The Dice score, a critical metric for evaluating segmentation performance, measures the spatial overlap between predicted and ground truth regions.

Interpreting the Dice scores provides significant insights into the segmentation accuracy and robustness of the deep learning models. Higher Dice scores, closer to 1, indicate strong agreement between actual and predicted tumor regions, reflecting superior segmentation performance. Variations in Dice scores across different tumor regions Tumor Core (TC), Whole Tumor (WT), and Enhanced Tumor (ET)-highlight the models' abilities to differentiate tumor subtypes and accurately capture tumor boundaries.

Based on the Dice scores, it can be inferred that deep learning models such as 3D fully convolutional networks (3D FCNs), ResNet models, AGSE-VNet models, and encoder-decoder CNN architectures exhibit high segmentation accuracy for brain tumor images. Consistently high scores across multiple studies suggest the reliability and effectiveness of these models in accurately identifying and delineating tumor regions. However, lower scores in specific regions indicate areas where further refinement, such as enhanced model architectures or dataset augmentation, is required to improve segmentation performance.

CONCLUSION

In conclusion, this brief yet critical review highlights significant advancements in the application of deep learning methods for brain tumor image segmentation within medical imaging technology. The promising results achieved by deep learning-based segmentation approaches underscore their potential to enhance diagnostic capabilities for brain tumor detection and analysis. Continued research and development in this field hold immense promise for advancing medical imaging practices and ultimately benefiting patient care through more accurate and efficient tumor segmentation techniques.

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