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EFFICIENT BRAIN TUMOR SEGMENTATION USING LIGHTWEIGHT PSEUDO-3D UNET++ MODEL

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ABSTRACT

Accurate Brain tumor segmentation from magnetic resonanceimages (MRIs) is of paramount importance for clinical treatment decisions and surgical planning. Recent advancements have shown promising results indeep convolutional networks for this task. Often rely state-of-the-art models on computationally expensive 3D convolutions and complex ensemble strategies, which pose challenges in terms of computational overhead and system complexity. Additionally, resource constraints necessitate the pursuit of high accuracy within limited computational budgets. In this research, we propose a novel methodology to address the challenges in brain tumor segmentation using the 3D UNet++.This model is a lightweight and efficient pseudo-3D model designed to segment 3D volumetric images in a single pass. 3D UNet++ model builds upon the popular U-Net architecture by incorporating 3D convolutional layers to capture spatial information. It achieves efficient segmentation by performing computations in a single pass, making it suitable for real-time applications. Based on the U-Net architecture, 3D UNet++ enhances the representation capabilities by utilizing dense skip connections and nested U-Net architectures. It efficiently captures spatial information in a hierarchical manner, improving the segmentation accuracy of volumetric images. To evaluate the efficacy of our methodology, we shown extensive experiments on the BraTS 2018 dataset, a widely recognized benchmark for brain tumor segmentation. Performance metrics, such as Dice similarity coefficient (DSC) and sensitivity, were employed to assess the robustness and accuracy of our proposed method.

KEYWORDS: *Brain tumor segmentation, BraTS, 3D UNet++, Deep convolutional network.*

1. INTRODUCTION

Accurate segmentation of brain tumors from magnetic resonance images (MRIs) plays a crucial role in clinical treatment decisions and surgical planning [1]. The ability to precisely identify and delineate tumorregions assists medical professionals in determining appropriate treatment strategies and monitoring disease progression [2,3]. In currentyears, particularly the use of deep convolutional networks advancements in deep learning techniques have shown great promise in achieving accurate segmentation results for this task.

However, state-of-the-art models often employ computationally expensive 3D convolutions and complex ensemble strategies, which bring about challenges in terms of computational overhead and system complexity [4]. These resource-intensive approaches require substantial computational resources and may not be feasible within limited computational budgets or in resource-constrained clinical settings [5]. Therefore, there is a growing need to develop accurate brain tumorsegmentation models that can achieve high performance while operating within practical computational constraints.
The architecture of 3D Unet++ model for Brain tumor segmentation makes several significant contributions:

- Proposing a lightweight and efficient pseudo-3D UNet++ model capable of segmenting 3D volumetric brain tumor images in a single pass. This addresses the computational overhead and complexity challenges associated.
- Enabling real-time segmentation of brain tumordue to the model's computational efficiency, making it suitable for practical clinical applications.

The paper consists of five sections. Section 2 reviews existing brain tumor segmentation methods, highlighting their strengths and limitations, and justifying the need for the proposed efficient lightweight pseudo-3D UNet++ model. Section 3 describes the architecture of the model, incorporating 3D convolutions, dense skip connections, and nested U-Net structures for efficient brain tumor segmentation. Section 4 presents a comparative analysis, evaluating the proposed model's performance against existing methods using metrics like DSC, sensitivity, and specificity. Section 5 summarizes key findings, emphasizes the importance of accurate brain tumor segmentation, discusses how the model addresses computational challenges, and suggests potential future work for further improvements.

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2. RELATED WORKS

Some of the papers based on the brain tumor segmentation are reviewed below,
In their work, Isensee*et al.* [6] utilized the nnU-Net architecture for BraTS 2020 segmentation, making BraTS-specific modifications, including postprocessing, region-based training, and more aggressive techniques, to notably improve segmentation performance beyond the baseline configuration.

Wang *et al.* [7] exploredTransBTS, a novel network applying Transformer in 3D CNN for MRI brain tumor segmentation. The encoder-decoder structure combined 3D CNN and Transformer for global feature modeling, utilizing data augmentation and minor adjustments to the nnU-Net pipeline.

Huang *et al.* [8] combined Dempster-Shafer theory and deep learning, proposing a semi-supervised algorithm that utilized image transformation and probabilistic/evidential neural networks in parallel to enhance brain tumor segmentation by fusing multiple sources of evidence and addressing limited labeled data challenges.

Vijay *et al.* [9] proposed the SPP-U-Net was introduced, replacing residual connections with a combination of Spatial Pyramid Pooling (SPP) and Attention blocks, expanding reconstruction scope and incorporating local and global context for brain tumor segmentation, without heavy approaches like nested and dense skip connections and transformers used in existing literature.

Fang and Wang [10] proposed an integrated block and aggregation connection for efficient and accurate tumor structure segmentation by incorporating mask images to enhance spatial relationships and using a multi-scale convolution kernel to extract local tumor information, preserving geometric spatial relationships and implicitly integrating context information.
Mei *et al.*[11] demonstrated the significant improvement in discriminative power of image segmentation models through the identification of partial common information. Specifically, they introduced a novel concept called the partial common information mask (PCI-mask), which provided a detailed characterization of the shared partial common information among subsets of modalities. This module selectively weighted different feature representations in multi-modal data, leveraging the identified partial common information to enhance segmentation performance.

Balamurugan and Gnanamanoharan [12] proposed a hybrid DCNN classifier, enhancing the LuNet algorithm, to identify tumor areas and classify brain tumors as benign or malignant, utilizing GLCM, VGG16, and LOG for feature extraction and pretreatment to improve non-deep learning classifiers' performance.

Ramasamy *et al.*[13] developed an efficient deep learning model for semantic segmentation, utilizing a multi-modal modifier Link-Net architecture with a squeeze and Excitation ResNet152 backbone, was developed, evaluated, and compared with traditional state-of-the-art models, and its performance was verified by neurosurgeons at Manipal Hospital in Bangalore.

Poonguzhali*et al.*[14] introduced the ADRU-SCM is an Automated Deep Residual U-Net Segmentation with Classification model for Brain Tumor Diagnosis, incorporating wiener filtering (WF) based preprocessing to remove noise, a deep residual U-Net for segmentation, and VGG-19 as a feature extractor for brain tumor segmentation and classification.

Sharma *et al.*[15] proposed the DOBES algorithm, integrating Dynamic Opposition Learning (DOL), resolved issues in the original BES algorithm, and a hybrid multilevel thresholding image segmentation approach was developed for MRI images, utilizing DOBES for thresholding and morphological operations to eliminate unwanted areas.

Reddy and Dhuli [16] comprised the three phases: pre-processing (skull-stripping and image data augmentation), classification (using a lightweight CNN to identify normal or abnormal brain MR images), and segmentation.

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Table 1: Comparative analysis of the existing methods on brain tumour segmentation

Authors	Methods Used	Advantages	Disadvantages
Isenseeet *al.* [6]	nnU-Net	-Improved segmentation performance with BraTS-specific modifications.	- Potential increase in Complexity and computational requirements.
Wang *et al.*[7]	TransBTS	-Enhanced Segmentation by leveraging the power of Transformer for global feature modeling.	- Increased complexity and potential computational requirements due to the combination of 3D CNN and Transformer in the TransBTS network.
Huang *et al.*[8]	SEFNet	-It combines multiple sources of evidence and leverages semi-supervised learning to enhance segmentation performance.	-The integration of Dempster-Shafer theory and deep learning introduces complexity and potentially reduces interpretability of the segmentation model.
Vijay *et al.*[9]	SPP-U-Net	-It replaces residual connections with SPP and Attention blocks,enhancing the scope of reconstruction and incorporating local and global context.	-Limitations compared to mheavy approaches like nested skip connections and transformers in terms of capturing intricate relationships and complexities within the data.
Fang and Wang [10]	Unet	-improves Segmentation accuracy by leveraging spatial relationship information and extracting.	-may limit the applicability of the proposed approach to other orientations or may overlook relevant information.
Mei *et al.*[11]	U-net	-Self attention module enhances the Discriminative power of image segmentation models by selectively weighting feature representations.	-Identification and characterization of partial common information, which may pose challenges in scenarios where the shared information is ambiguous or difficult to discern
Balamurugan and Gnanamurugan [12]	DCNN	-to improve the performance of non-deep learning classifiers for brain tumor classification and localization.	-Limitations in scenarios with complex tumor variations or when dealing with large-scale datasets, which may require more advanced deep learning architectures or additional preprocessing techniques.
Ramasamy *et al.*[13]	LinkNet	-Squeeze and Excitation ResNet152 Backbone enhances theefficiency and accuracyof semantic segmentation.	-The applicability and generalizability of the developed model may be limited to the specific dataset and setting used in the evaluation.
Poonguzhali*et al.*[14]	ADRU-SCM	-It combines wiener filtering, deep residualU-Net segmentation,and VGG-19 feature extraction to provide an automated and accurate approach for brain tumor segmentation.	-VGG-19 may limit the model's generalizability to different datasets or require additional adaptation and validation for diverse clinical scenarios.

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Sharma *et al.*[15]	DOBES	-It improves the efficiency and effectiveness of multilevel thresholding for MRI image segmentation.	-Performance and generalizability may be dependent on the specific benchmark images used for evaluation.
Reddy and Dhuli [16]	CNN	-The proposed work's inclusion of pre-processing, data augmentation, and it improves the accuracy and efficiency of brain MR image.	-Dependent on the accuracy of the skull-stripping process and the generalizability of the method used to different datasets and pathological conditions.

3. PROPOSED LIGHTWEIGHT PSEUDO-3D UNET++ MODEL

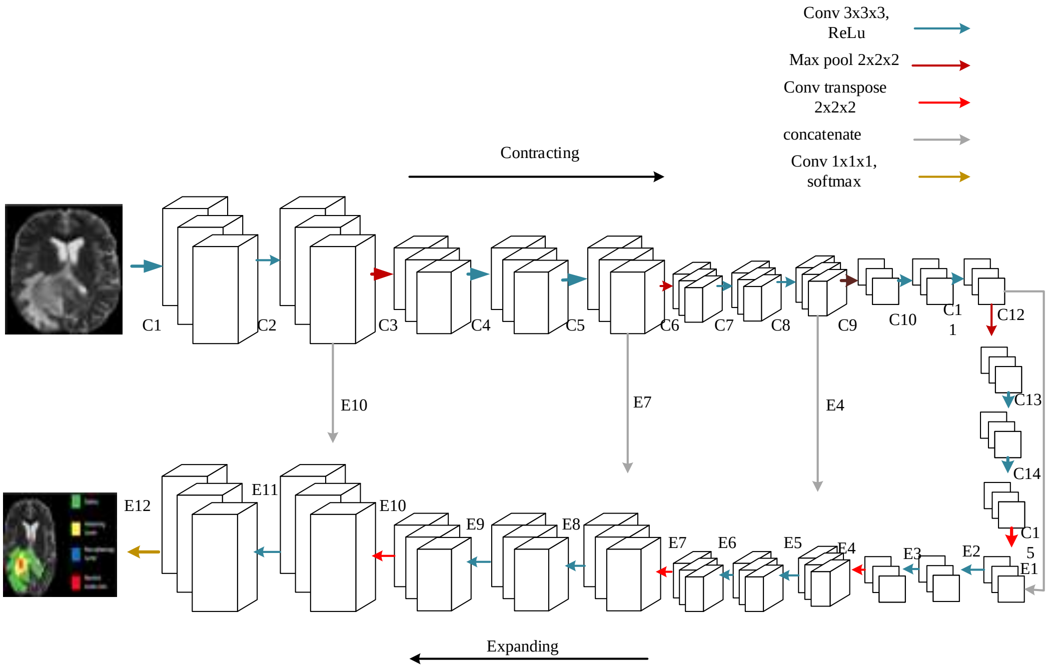

Figure 1: Architecture of the proposed lightweight pseudo-3D UNet++ model

We propose a novel methodology to address the challenges of brain tumor segmentation using the lightweight pseudo-3D UNet++ model. Our approach aims to achieve accurate segmentation while operating within limited computational budgets and reducing system complexity.The foundation of our methodology is the 3D UNet++ model, which is an extension of the widely used U-Net architecture. The U-Net architecture has demonstrated excellent performance in medical image segmentation tasks. The 3D UNet++ further enhances the representation capabilities by incorporating dense skip connections and nested U-Net architectures. These additions enable the model to capture spatial information in a hierarchical manner, improving the accuracy of tumorsegmentation in volumetric images.To address the computational overhead associated with traditional 3D convolutions, we employ a lightweight pseudo-3D approach. Unlike computationally expensive 3D convolutions that process the entire 3D volume, our model operates in a pseudo-3D manner by processing 2D slices sequentially. This enables us to achieve efficient segmentation while reducing the computational burden.Our proposed methodology performs computations in a single pass, enabling real-time applications and reducing inference time. Byleveraging the pseudo-3D approach and the efficient design of the 3D UNet++ model, we achieve accurate segmentation results without sacrificing computational efficiency.

3.1 Data Preprocessing

The MRI scans are preprocessed to ensure consistency and enhance the quality of the input data. Preprocessing steps may include intensity normalization, skull stripping, and spatial resampling to achieve a standardized format.Intensity normalization addresses variations in intensity scales across different scanners and sites. Skull stripping removes non-brain tissues for brain region isolation. Spatial resampling adjusts spatial resolution to match desired coordinates or resolutions for further analysis or visualization in various fields like remote sensing and image processing.

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Normalized_value = (Original_value - Mean) / Standard_Deviation

3.2 Patch Extraction

To efficiently train the pseudo-3D UNet++ model and handle memory constraints, 3D patches are extracted from preprocessed MRI volumes, representing local and spatially contiguous portions of the image. This approach allows for focused analysis of smaller regions and enables independent processing or training for tasks like classification, segmentation, or feature extraction, contributing to a coherent understanding of the entire image or dataset.

3.3 Lightweight Pseudo-3D UNet++ Architecture

The architecture is designed for efficient segmentation of brain tumorfrom 3D volumetric MRI images. It is an extension of the popular U-Net architecture, incorporating 3D convolutional layers to capture spatial information effectively. An encoder-decoder structure follows the model with dense skip connections and nested U-Net architectures. These connections enable the efficient capture of spatial features in a hierarchical manner, leading to improved segmentation accuracy. By performing computations in a single pass, the model achieves efficiency, making it suitable for real-time applications and overcoming the challenges posed by resource constraints.

3.3.1 Training the Lightweight Pseudo-3D UNet++ Model

The extracted 3D patches, along with corresponding ground truth segmentation masks, are used to train the lightweight pseudo-3D UNet++ model. During training, the model learns to capture relevant spatial features and accurately segment brain tumors. As Data Preparation, The training data is prepared by selecting a set of input 3D volumes and their corresponding ground truth segmentation masks from the BraTS 2018. AsNetwork Architecture, The architecture of the Pseudo-3D UNet++ model, based on the U-Net with 3D convolutional layers and dense skip connections. This encoder-decoder structure enhances spatial feature capture. Use stochastic gradient descent (SGD) or its variants as the optimization algorithm. SGD updatesthe model parameters iteratively using mini-batches of training samples, making it computationally efficient and scalable. Feed the preprocessed data into the Pseudo-3D UNet++ model. During training, the model learns to accurately segment brain tumors by capturing relevant spatial features. Fine-tune hyperparameters like learning rate, batch size, and the number of epochs through experimentation to optimize the training process. Implement techniques like dropout or batch normalization to prevent overfitting and improve generalization. Assess the model's accuracy and robustness using performance metrics such as DSC and sensitivity on the BraTS 2018 dataset. The Pseudo-3D UNet++ model efficiently captures spatial information in a hierarchical manner, making it suitable for real-time applications and addressing the challenges of brain tumor segmentation within limited computational budgets.

Dense skip connections

Dense skip connections link corresponding layers in the encoder and decoder, facilitating seamless information flow and spatial feature propagation. They preserve fine-grained details during upsampling, enhancing segmentation accuracy**.**

Nested Architecture

The 3D UNet++ uses nested U-Net structures, stacking multiple U-Net architectures, capturing spatial information hierarchically. Each nested U-Net captures features at different abstraction levels, improving the model's ability to segment brain tumors accurately.

4. EXPERIMENTAL RESULTS

Performance evaluation involves assessing the accuracy and robustness of the pseudo 3D UNet++ model for segmentation of brain tumor. Using metrics such as DSC and sensitivity, the model's segmentation results are compared from the BraTS 2018 datasetwith ground truth segmentations. The evaluation process validates the model's effectiveness and its potential for clinical applications.
Dice Similarity Coefficient

$$\left(2 * |B \cap A|\right) / \left(|B| + |A|\right)$$

It is a statistical measure commonly used to evaluate the similarity or overlap between two sets or regions in a binary segmentation task. It is calculated as twice the intersection of the sets divided by the sum of the sizes of the two sets, providing a value between 0 (no overlap) and 1 (perfect overlap) to assess the accuracy of segmentation results.
Sensitivity

$$\text{Sensitivity} = TP / (FN + TP)$$

It is also known as recall or true positive rate, is a statistical metric used to evaluate the performance of a binary classification or segmentation model. It measures the proportion of positive cases correctly identified by the model out of all the actual positive cases

Comparative Analysis

Table 2 indicates the performance of proposed Lightweight pseudo 3D-Unet++ model with existing methods such as U-Net [11] and MM-LinkNet [13]. The proposedLightweight pseudo 3D-Unet++ model achieved the better segmentation performance than

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other methods for Brain Tumor Segmentation. Our method achieves Dice coefficient value of 0.912% and Sensitivity value of 0.925%

Table: 2 Dice coefficient and Sensitivity for proposed and existing methods

Methods	Dice coefficient (%)	Sensitivity (%)
U-net [11]	0.829	0.887
MM-LinkNet [13]	0.777	0.766
Proposed 3D-Unet++	0.912	0.925

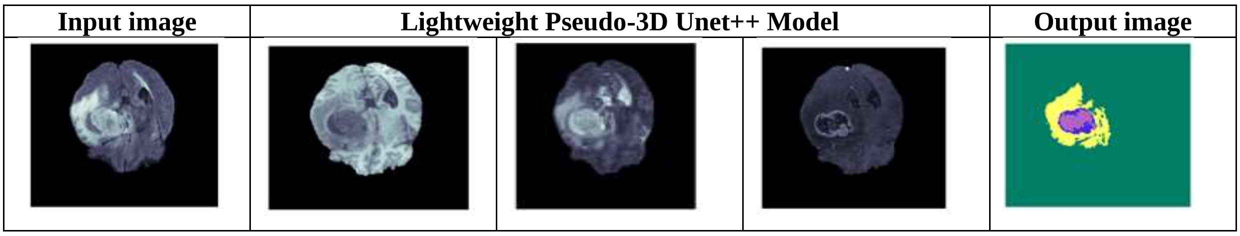

Figure: 2 Segmentation Results

Figure 2 presents the segmentation results obtained from the Lightweight Pseudo-3D Unet++ model in the context of brain tumor segmentation. The figure showcases the model's performance in accurately delineating tumor regions within the magnetic resonance images (MRIs) of the brain. Each subfigure in Figure 2 displays a pair of images side by side: the original MRI slice from the dataset on the left and the corresponding segmentation mask generated by the Lightweight Pseudo-3D Unet++ model on the right.

5. CONCLUSION

In this paper, lightweight pseudo-3D UNet++ model demonstrates significant advancements in accurate brain tumor segmentation, outperforming state-of-the-art models. By efficiently capturing spatial features in a hierarchical manner, our approach addresses computational challenges and offers potential for real-time clinical applications with improved segmentation accuracy on the BraTS 2018 dataset.

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