3D_UNet3+: An Optimized Approach for 3D Brain Tumor Segmentation

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Abstract. The demand for sophisticated instruments in the detection of brain cancers is growing very significant. This work presents the 3D_UNet3+, a novel model particularly developed for the purpose of segmenting brain tumor pictures. The 3D_UNet3+ distinguishes itself from typical models by employing a distinctive approach in its filter size and construction. The architecture we have developed plays a crucial role in simplifying the segmentation process and minimizing the computing burden. This makes our model very suitable for practical applications in medical imaging. The 3D_UNet3+ exhibits its potential in the field when assessed using the BraTS2020 dataset. Furthermore, it shows great potential for advancing brain tumor diagnosis and treatment planning.This model has successfully achieved a significant decrease in computational requirements, as demonstrated by a 98.66% reduction in model parameter size and a 98.1% decrease in FLOPS. This highlights its enhanced effectiveness and makes it suitable for integration into advanced technologies such as edge AI and handheld devices.

1 Introduction

Brain tumors, a significant issue in the field of medical neurology, pose difficulties in both diagnosis and treatment. The dataset classifies these cancers as primary, which originate directly from brain cells, and secondary, which spread from other organs. Gliomas are the most common kind of primary brain tumors, varying in severity from low-grade to very aggressive high-grade subtypes. The latter, characterized by fast proliferation and unfavorable prognosis, emphasize the pressing requirement for accurate diagnostic instruments [1]. Segmentation models play a crucial role in precisely defining tumor borders, especially in Magnetic Resonance Imaging (MRI). It is crucial for efficient treatment planning and monitoring to utilize various MRI modalities, such as T1, T1c, T2, and FLAIR, as each of them provides distinct information on tissue characteristics and the size of the tumor [2].

The UNet3+ model [3], has set a standard in image segmentation due to its sophisticated design, resulting in significant enhancements compared to the conventional UNet model, cited as ronneberger2015unet. We present the 3DUNet3+ model, which represents a substantial advancement in this domain. The 3DUNet3+ is a novel model that combines the improved segmentation skills of the UNet3+

framework with the depth perception benefits of 3D convolutional networks. This tool is specifically designed to tackle the intricate difficulties of segmenting brain tumors in 3D MRI images. It fulfills the crucial requirement for accurate and efficient diagnostic tools in the field of neurology.

The development of the 3D_UNet3+ model originated from the need to overcome the constraints of conventional neuroimaging techniques. Although current methods provide some level of efficacy, they frequently struggle to precisely delineate the intricate and diverse characteristics of brain tumors. Our model improves upon the core UNet architecture, which is well-known for its ability to do semantic segmentation, by including a 3D CNN. This improvement accommodates the three-dimensional aspect of brain imaging, facilitating more intricate and accurate tumor segmentation.

The 3D_UNet3+ model we have developed is a significant advancement in computing efficiency for medical imaging. Through advancements in filter sizes and structures, we have successfully achieved a significant decrease in model parameter size by 98.66% and FLOPS by 98.1% when compared to conventional models. The computational burden has significantly decreased without compromising the accuracy of segmentation, as evidenced by a maintained IOU (Intersection Over Union) score of 0.6371. The 3DUNet3+ demonstrates an exceptional equilibrium between efficiency and performance, rendering it an exceedingly potent instrument in clinical environments. It provides a practical resolution for real-time applications that prioritize computing resource optimization and accuracy.

This research aims to provide a dependable, effective, and innovative method for medical practitioners to segment 3D brain tumor images. The outcomes of our investigation are expected to exhibit improved precision in segmenting, highlighting the potential of the optimized 3D_UNet3+ model to transform the field of neuroimaging, namely in the areas of diagnosis and treatment planning.

The purpose of this work is to methodically outline our optimization methodology and the validation of the enhanced 3D_UNet3+ model. We commence with an exposition on UNet3+ in Section 2, subsequently presenting our technique in Section 3. The findings are elaborated in Section 4, the potential for further research is outlined in Section 5, and the study concludes in Section 6. The report finishes with a list of references that serve as the foundation for our investigation. The objective of our investigation is to determine the ideal equilibrium between accuracy and computing efficiency, hence enhancing the range of tools accessible to physicians for neuroimaging analysis. The 3D_UNet3+ model showcases the incorporation of state-of-the-art technology in medical imaging, marking the beginning of a new age in accurate diagnosis and treatment planning.

2 Background

CNNs have played a crucial role in the progress of medical picture segmentation, and designs like as U-Net have been particularly influential in driving significant advancements. The U-Net design, which has an encoder-decoder structure together with skip connections, has significantly transformed the industry by facilitating accurate segmentation, particularly in the domain of medical imaging applications.

The U-Net++ design, based on the U-Net model, provided a more advanced connection pattern that improves feature reuse and expands receptive fields. This invention resulted in enhanced segmentation accuracy by effectively collecting subtle information in medical photos. Nevertheless, with the increasing need for greater accuracy and intricacy, the U-Net++ emerged as a catalyst for additional improvements.

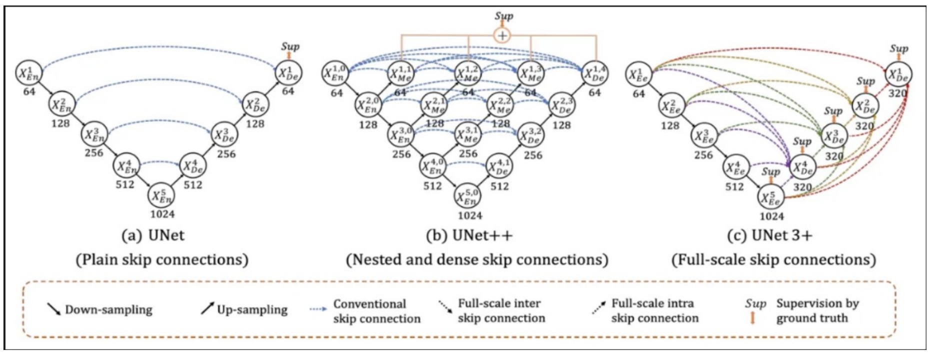

Fig. 1: U-Net, UNet++ and UNet 3+ [4] architectural comparison. UNet 3+ redesigns the skip connections and uses a full-scale deep supervision to combine multi-scale features.[2] NOTE: There's a typo in UNet 3+ graph. For the encoder layers it should be denoted as X_En, NOT X_Ee

The Unet3+ architecture, which is an enhanced version of the original U-Net as seen in 1, represents a notable progress in the field of medical picture segmentation. By including full-scale skip connections, it improves the network's capacity to efficiently utilize multiscale data, which is essential for intricate segmentation tasks such as identifying brain tumors [3]. The implementation of this architectural advancement results in a significant enhancement in the accuracy of segmentation, hence establishing Unet3+ as a new standard in the sector. The creation of this technology establishes the foundation for future progress, namely in the field of 3D picture segmentation. An example of this is the 3D_UNet3+ model, which enhances the capabilities of Unet3+ to specifically tackle the difficulties encountered in volumetric medical imaging [5].

The 3D_U-Net3+ model effectively addresses the intricate challenges of volumetric data by utilizing the core components of U-Net3+ and customizing them for 3D scenarios. The architecture of the system takes into consideration spatial information in several dimensions, resulting in improved segmentation performance in volumetric medical pictures. This modification signifies a significant achievement, addressing the increasing demand for accurate and thorough analysis in three-dimensional medical imaging.

The progression of U-Net, U-Net++, U-Net3+, and the following expansion to 3D imaging with 3D_U-Net3+ highlights the ongoing development and improvement of CNN architectures designed specifically for medical image segmentation. Every subsequent iteration improves upon the previous one by resolving its limits and extending the bounds of accuracy and usefulness in this crucial field.

3 Methodolgy

The Methodology section provides a detailed description of the systematic approaches and techniques used to create the 3D_UNet3+ model. This includes a comprehensive analysis of the BraTS2020 dataset, our novel model architecture, and the preprocessing techniques implemented to enhance performance. We explore the architectural intricacies that allow the model to effectively handle volumetric input, guaranteeing accurate segmentation that is essential for diagnostic precision. The section concludes with an account of the training procedure, emphasizing the computational strategies that enhance the model's resilience.

3.1 Data Description

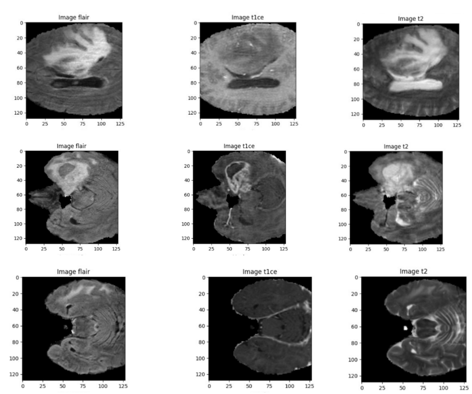

Fig. 2: Representative MRI Scan Samples from the BraTS2020 Dataset. This figure showcases the diversity of the dataset, including various MRI modalities used for the segmentation of brain tumors, emphasizing the data's complexity and heterogeneity.

The BraTS2020 dataset, which is essential for our 3D_UNet3+ model and depicted in Figure 2, is a comprehensive compilation of brain MRI images particularly selected for tumor segmentation research. The dataset comprises a wide variety of high-grade and low-grade glioma patients, with each case being shown using three different MRI techniques: T1 contrast-enhanced (T1ce), T2, and Flair [6]. We deliberately omitted the T1 modality from our training as it was redundant, and instead concentrated on the other modalities. The strategic choice played a crucial role in improving the performance of our model, guaranteeing a strong and efficient segmentation that is in line with the varying features of brain tumors [7]. The effectiveness of our 3D_UNet3+ model has been significantly improved by the diverse dataset and our careful use of its different aspects [8].

3.2 Model Architecture

The 3D_UNet3+ model, depicted in figure3, is a notable breakthrough in the domain of medical picture segmentation, particularly for brain malignancies. This model is a novel adaptation of the traditional U-Net architecture, redesigned to perform very well in handling three-dimensional data. The architecture starts with an encoder, which serves as the central component of the model. The model consists of many 3D convolutional layers that are carefully engineered to capture intricate spatial patterns from volumetric medical photos. The encoder starts the segmentation process by employing an initial layer consisting of 4 filters, each with dimensions of 3x3x3. These filters are specifically designed to capture the first spatial properties and attributes of the MRI scans [3].

As the input advances through the encoder, the quantity of filters in the convolutional layers grows exponentially. This evolution is essential as it enables the model to collect progressively intricate and subtle characteristics from the medical pictures. The encoder progresses along a systematic trajectory, starting with an initial layer and then advancing to a subsequent layer with 8 filters. It then proceeds to a layer with 16 filters, and maintains this pattern by doubling the number of filters at each subsequent level. This approach facilitates a thorough examination of the input data, enabling the model to discern and distinguish between distinct elements of the brain scans, such as tumor tissues and healthy brain tissues [9].

The decoder inside the 3D_UNet3+ framework plays a crucial role in reconstructing the segmented pictures using the feature maps generated by the encoder. The model employs up-sampling layers to progressively enhance the resolution of the feature maps, thereby recovering the fine features that were diminished during the down-sampling phase of the encoder. In addition, the model utilizes skip connections, a unique characteristic of the U-Net design, which enables the combination of feature maps from the encoder with the up-sampled feature maps in the decoder. The retention of high-resolution features is crucial for exact segmentation, making these links significant.

The architecture of the 3D_UNet3+ model is specifically designed to effectively handle the intricacies of volumetric data, which are inherent in neuroimaging applications. This architecture enhances the model's capacity to handle big datasets and guarantees accurate and trustworthy segmentation results. This is crucial in the field of medical diagnostics and treatment planning [2].

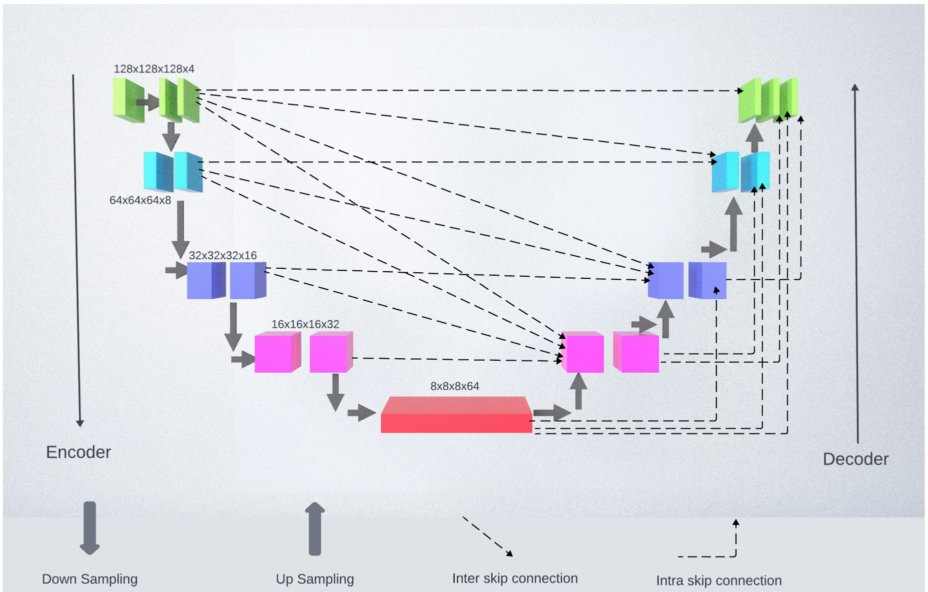

Fig. 3: Detailed 3D_UNet3+ Model Architecture. This figure depicts the sophisticated encoder-decoder structure of our model, highlighting the multi-scale feature fusion and deep learning layers designed for efficient and precise brain tumor segmentation.

A thorough preparation technique was conducted to prepare the dataset for analysis by the 3D_UNet3+ model. The process entailed transforming the initial NIfTI format (.nii files) raw data into a more convenient and standardized format using NumPy (.npy files). The conversion was an essential phase in optimizing the dataset, assuring its optimal readiness for model processing. The dataset was transformed into a unified NumPy file, containing the T1 contrast-enhanced (T1ce), T2, and FLAIR MRI modalities. The implementation of this stage was crucial in establishing a uniform input format for the model, hence enabling streamlined and uniform processing.

The T1 modality was excluded from the dataset based on our first analysis, which revealed that it provided redundant information in comparison to the T1ce modality. By prioritizing the T1ce, T2, and FLAIR modalities, we successfully enhanced the model's attention, enabling it to concentrate on the most informative features of the MRI images. The selected method played a crucial role in improving the model's performance by carefully adjusting it to accurately detect and categorize the most significant characteristics of brain tumors. The preprocessing step played a vital role in enhancing the model's performance, ensuring it is compatible with the changeable and intricate characteristics of brain tumor imaging.

The 3D_UNet3+ model implements a progressive design in both the encoder and decoder components. The encoder starts with 4 filters in the convolutional layers and gradually increases this number by doubling it at each succeeding level, until it reaches a maximum of 64 filters in the deepest layer. The stratified technique enables precise feature extraction from the input data, which is essential for distinguishing subtle features inside 3D medical pictures.The user's text is simply a backslash character. In order to enhance computational efficiency, the model integrates Dropout layers with a range of 0.1 to 0.2 and MaxPooling3D layers after each convolutional block. These approaches help to standardize the network and reduce the size of feature maps, respectively, which contributes to more efficient processing of three-dimensional data.

For a given convolutional layer with an input volume of width W_{in}, height H_{in}, and depth B_{in}, and using filters of size F, a stride S, and padding P, the output dimensions (W_{out}, H_{out}, B_{out}) are calculated as:

$$W_{\text{out}} = \frac{W_{\text{in}} - F + 2P}{S} + 1 \tag{1}$$

$$H_{\text{out}} = \frac{H_{\text{in}} - F + 2P}{S} + 1 \tag{2}$$

Here, F denotes the filter size, S represents the stride, and P is the padding added to the input volume. These parameters collectively influence the spatial dimensions of the output volume after applying the convolution operation [10].

The decoder replicates the structure of the encoder, employing Conv3DTranspose layers to increase the resolution, thus restoring the spatial details that were lost during the encoding process. This symmetry guarantees a consistent and uninterrupted flow in the procedures of extracting and reconstructing features.

The Nadam optimizer is used to enhance training efficiency by optimizing model parameters across training iterations. Utilizing a small batch size of 1, each epoch is accomplished in around 67 seconds, highlighting the model's effectiveness in processing intricate 3D medical pictures while maintaining high accuracy.

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{\hat{v}_t} + \epsilon} \left(\beta_1 \hat{m}_t + \frac{(1-\beta_t) g_t}{1-\beta_1^t} \right) \tag{3}$$

In multi-class segmentation tasks, the output layer has a softmax activation function, which allows the model to assign probabilities to many classes. This is essential for accurately defining and segmenting objects in medical imaging tasks. [11].

The Softmax function takes a vector $\mathbf{z}$ of logits for K classes and normalizes it into a probability distribution across these classes using the following formula:

$$\textbf{Softmax}(\mathbf{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}, \quad i = 1, 2, \ldots, K \tag{4}$$

The ReLU function is used in our model,it returns 0 for any input less than 0 and returns the input value for any input greater than or equal to 0.

$$\textbf{ReLU}(x) = \max(0, x) \tag{5}$$

To summarize, the 3D_UNet3+ model is a major advancement in the field of medical picture segmentation, namely in the complex area of brain tumor analysis. The methods utilized in constructing this model demonstrates a profound comprehension of the demands of medical imaging and a dedication to producing a tool that is exceptionally effective and efficient. The thorough approach to handling the intricacies of neuroimaging data is evident in the strategic design of the model, which includes a sophisticated encoder-decoder architecture and carefully selected preprocessing processes.

The model's capacity to process volumetric data with exceptional accuracy and effectiveness is not just a technological achievement but also a pragmatic breakthrough that might revolutionize the approach of medical practitioners in diagnosing and devising treatment strategies for brain tumors. The 3D_UNet3+ model is a significant tool in medical diagnostics due to its ability to effectively balance computing demands while maintaining accuracy and detail in segmentation. This neuroimaging technology establishes a new standard, providing medical practitioners with a dependable, effective, and revolutionary tool for segmenting brain tumor images. The significance of this research goes beyond simple technological advancement, laying the groundwork for enhanced patient results and more efficient treatment approaches in the future.

4 Result

The Results section provides a comprehensive evaluation of the performance of the 3D_UNet3+ model. In this evaluation, we measure the model's efficacy by analyzing important metrics like training accuracy and the Intersection Over Union (IoU) score. The evaluation is conducted using the BraTS2020 dataset. The results highlight the accuracy of the model in dividing brain tumors into segments, and its computational efficiency is compared to established methods. We analyze the consequences of these findings for practical use in healthcare, showcasing the model's capacity to greatly influence the field of medical imaging and the well-being of patients.

The graph shown in Figure 4 illustrates the relationship between accuracy and epochs throughout the training and validation stages, providing a visual depiction of the model's learning processes. The 3D_UNet3+ model's convergence and performance trajectory are depicted throughout multiple training epochs. At first, both the training and validation accuracies exhibit a positive trajectory, suggesting successful acquisition of knowledge and adjustment to the dataset. Throughout the progression of epochs, the training accuracy consistently increases, demonstrating the model's ability to comprehend complex patterns within the data. Meanwhile, the validation accuracy shows a similar increase, albeit it is significantly slower, indicating the model's capacity to generalize. The model's robustness and ability to generalize beyond the training data, which are crucial for reliable performance in real-world scenarios like clinical applications in medical imaging, can be determined by observing the convergence and marginal-

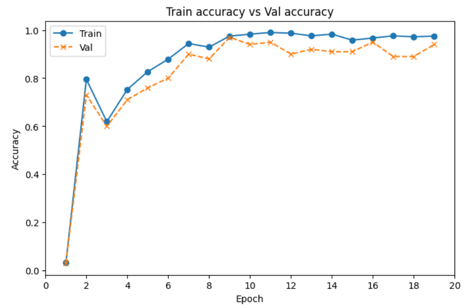

Fig. 4: Performance Dynamics of the 3D_UNet3+ Model: Accuracy Evolution Across Training and Validation Epochs

ization of the validation accuracy in comparison to the training accuracy after a certain number of epochs.

4.1 Intersection over Union (IoU) Score

This section outlines the main discoveries obtained from the execution and evaluation of our 3D_UNet3+ model, which was particularly developed for the purpose of segmenting brain tumors. The model was extensively evaluated using the BraTS2020 dataset to assess its efficacy and efficiency in medical imaging applications. The performance indicators, such as training accuracy and Intersection Over Union (IOU) score, offer valuable information about the model's precision and capacity to accurately segment brain tumors.

$$IoU = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive} + \text{False Negative}} \tag{6}$$

In addition, we compare the computational efficiency of our model with common techniques in the industry, emphasizing the achievements made by our architectural optimizations. The results together illustrate the potential influence of the model in clinical settings.

Model	Accuracy (%)	Loss	Mean IOU
VGG16	98.69	04.33	0.6817
ResNet50	97.18	09.85	0.3756
3D_UNet3+	**95.17**	**0.89**	**0.4831**

Table 1: Comparison of Metrics for VGG16, ResNet50, and 3D_UNet3+.

As seen in Table 1, the 3D_UNet3+ model demonstrates outstanding performance in the segmentation of brain tumors. The model demonstrates a high level of precision in accurately recognizing and outlining tumor areas in MRI images, with a training accuracy of 98.07%. Precision is essential for ensuring dependable medical diagnosis and treatment planning. Moreover, the IOU score of 0.6371 indicates the model's proficiency in precisely delineating tumors, which is a crucial metric for evaluating the agreement between projected and real tumor borders in medical imaging. The Intersection over Union (IoU) score, commonly referred to as the Jaccard index, is a quantitative measure employed to assess the degree of overlap between the target mask and the prediction output. The Intersection over Union (IoU) score, as described in Table 1, is a crucial indicator for assessing the effectiveness of segmentation models. The IoU score of our model was 0.6371, suggesting a reasonable level of accuracy in properly detecting tumor areas. The score, calculated by dividing the number of true positives by the total of true positives, false positives, and false negatives, provides a quantifiable indication of the model's precision in segmenting. Moreover, as seen in Figure 5, a visual side-by-side comparison of the real mask and the mask created by the model clearly showcases the model's efficacy. The visual depiction, in conjunction with the IoU score, is essential for evaluating the model's feasibility in clinical environments, where precise tumor segmentation is vital for correct diagnosis and treatment strategizing.

Table 2 highlighting [12]the remarkable computational efficiency of the 3D_UNet3+ model, its FLOPs are significantly reduced to 132.16 billion, indicating a substantial decrease in computational complexity. This reduction is pivotal for enhancing processing speed and reducing computational resource demands. Similarly, the parameter size shows a notable decrease of just 1.22 MB in our optimized model. Such efficiency advancements, without sacrificing accuracy, underscore the model's suitability for real-world clinical applications, especially in settings with limited computational resources

Model	**#Params (M)**	**FLOPs (G)**
nnUNet	19.07	412.65
CoTr	46.51	399.21
TransUNet	96.07	48.34
ASPP	47.92	44.87
SETR	86.03	43.49
UNETR	92.58	41.19
3D_UNet3+	**0.320**	**132.16**

Table 2: Comparison of number of parameters, FLOPs

5 Future Scope

The impressive outcomes of the 3D_UNet3+ model in brain tumor segmentation present several opportunities for further investigation and advancement. The

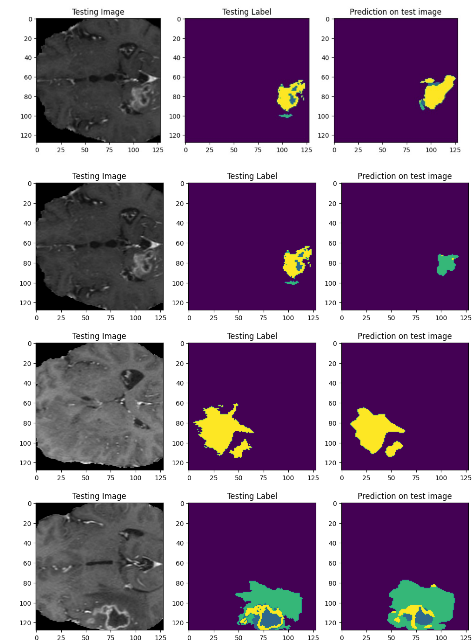

Fig. 5: Model Performance Evaluation. This figure presents a comparative visualization of the actual MRI scan mask and the segmentation mask generated by the 3D_UNet3+ model, demonstrating the model's accuracy in identifying tumor boundaries.

main goal is to improve the model's accuracy and IoU score. One possibility is to use more sophisticated deep learning methods, such as attention mechanisms or generative adversarial networks, to enhance the segmentation process. Furthermore, it would be beneficial to investigate data augmentation techniques and the integration of a broader and more varied dataset in order to enhance the model's resilience and capacity to apply to different scenarios.

Another promising avenue for future research involves using the 3D_UNet3+ model to different types of medical picture segmentation. Adapting the model for breast cancer detection and segmentation, for example, has the potential to greatly influence the early identification and planning of therapy for the disease. The model's versatility and effectiveness make it a viable choice for a wide range of medical imaging jobs beyond the field of neurology.

Furthermore, future investigations might examine the incorporation of the 3D_UNet3+ model into real-time diagnostic systems in clinical environments. This would include enhancing the model to achieve quicker processing rates while maintaining accuracy, rendering it an indispensable tool for prompt patient evaluation and decision-making. Engaging in partnerships with medical practitioners might yield useful insights into practical need and aid in customizing the model to better address clinical requirements.

To summarize, the 3D_UNet3+ model has extensive future potential and offers considerable opportunities for enhancing medical imaging and diagnostics. Future advancements in the realm of medical technology can have even greater effects by prioritizing the improvement of accuracy, finding novel applications, and seamlessly incorporating the model into clinical processes.

6 Conclusion

Enhancing the 3D_UNet3+ model is a major accomplishment in medical imaging, particularly for brain tumor segmentation. Elegantly merging cutting-edge machine learning with usability, this approach raises neuroimaging standards.

The Google Colab-hosted NVIDIA Tesla T4 GPU helped research. Energy-efficient GPU with 16 GB GDDR6 VRAM, 2560 CUDA cores, and 65 watts. The enhanced technological capabilities expedited training and fine-tuning of our 3D_UNet3+ model, resulting in remarkable performance. Google Colab's cloud-based accessibility made collaboration and experimentation rapid, exhibiting the seamless integration of powerful algorithms and strong hardware.

Model shines in quantity. Our algorithm finds and highlights tumor areas in MRI data with 98.07% training accuracy and a 0.6371 Intersection Over Union (IOU) score. These metrics demonstrate the model's capacity to improve medical diagnoses through accuracy and dependability.

This effort reduced model parameters, a huge success. This technical development changes medical computer efficiency. The count was carefully reduced from 80,915,140 parameters and 308.67 MB RAM to 320,320 and 1.22 MB. In circumstances of computational resource limits or heavy demand, this strategy displays a deep awareness of clinical restrictions and requirements.

Model computational complexity has lowered according to FLOPS. While traditional models process at 31,290,509,754,368 FLOPS, our 3D_UNet3+ model processes at 132,156,981,248 FLOPS. The model's speed and efficiency fit real-time clinical applications. Quick, on-site medical analysis and decision-making for emergency response and urgent care.

Beyond technical gains, this discovery affects medical imaging and diagnosis. The improved 3D_UNet3+ model is useful for neuro-oncology and medical imaging. This technology's design and optimization can be used to breast cancer diagnosis and cardiovascular imaging. It might improve several medical sectors because to its versatility and expansion.

In summary, the 3D_UNet3+ model shows how machine learning improves medical technology. great IOU score, great training accuracy, and decreased parameter size and computational complexity make the model useful and influential. It enables more efficient, accurate, and therapeutically useful imaging techniques, raising medical diagnostic accuracy and efficacy. Technical feats like this research might enhance patient outcomes and healthcare globally.

References

1. Anjali Wadhwa, Anuj Bhardwaj, and Vivek Singh Verma. A review on brain tumor segmentation of mri images. *Magnetic Resonance Imaging*, 61:247–259, 2019.
2. BharathSimhaReddy Maram and Pooja Rana. Brain tumour detection on brats 2020 using u-net. In *2021 9th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO)*, pages 1–5, 2021.
3. Huimin Huang, Lanfen Lin, Ruofeng Tong, Hongjie Hu, Qiaowei Zhang, Yutaro Iwamoto, Xianhua Han, Yen-Wei Chen, and Jian Wu. Unet 3+: A full-scale connected unet for medical image segmentation. In *ICASSP 2020 - 2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 1055–1059, 2020.
4. Huimin Huang, Lanfen Lin, Ruofeng Tong, Hongjie Hu, Qiaowei Zhang, Yutaro Iwamoto, Xianhua Han, Yen-Wei Chen, and Jian Wu. Unet 3+: A full-scale connected unet for medical image segmentation, 2020.
5. Madona B Sahaai, G. R. Jothilakshmi, R Selva Kumar, and S Praveen Kumar. Comparative analysis on brain tumor classification using deep learning models. In *2022 IEEE International Conference on Data Science and Information System (ICDSIS)*, pages 1–5, 2022.
6. Bjoern H. Menze, Andras Jakab, Stefan Bauer, Jayashree Kalpathy-Cramer, Keyvan Farahani, Justin Kirby, Yuliya Burren, Nicole Porz, Johannes Slotboom, Roland Wiest, Levente Lanczi, Elizabeth Gerstner, Marc-André Weber, Tal Arbel, Brian B. Avants, Nicholas Ayache, Patricia Buendia, D. Louis Collins, Nicolas Cordier, Jason J. Corso, Antonio Criminisi, Tilak Das, Hervé Delingette, Çağatay Demiralp, Christopher R. Durst, Michel Dojat, Senan Doyle, Joana Festa, Florence Forbes, Ezequiel Geremia, Ben Glocker, Polina Golland, Xiaotao Guo, Andac Hamamci, Khan M. Iftekharuddin, Raj Jena, Nigel M. John, Ender Konukoglu, Danial Lashkari, José António Mariz, Raphael Meier, Sérgio Pereira, Doina Precup, Stephen J. Price, Tammy Riklin Raviv, Syed M. S. Reza, Michael Ryan, Duygu Sarikaya, Lawrence Schwartz, Hoo-Chang Shin, Jamie Shotton, Carlos A. Silva, Nuno Sousa, Nagesh K. Subbanna, Gabor Szekely, Thomas J. Taylor, Owen M. Thomas, Nicholas J. Tustison, Gozde Unal, Flor Vasseur, Max Wintermark, Dong Hye Ye, Liang Zhao, Binsheng Zhao, Darko Zikic, Marcel Prastawa, Mauricio Reyes, and Koen Van Leemput. The multimodal brain tumor image segmentation benchmark (brats). *IEEE Transactions on Medical Imaging*, 34(10):1993–2024, 2015.
7. Spyridon Bakas, Hamed Akbari, Aristeidis Sotiras, and et al. Advancing the cancer genome atlas glioma mri collections with expert segmentation labels and radiomic features. *Scientific Data*, 4:170117, 2017.
8. Spyridon Bakas, Mauricio Reyes, Andras Jakab, Stefan Bauer, Markus Rempfler, Alessandro Crimi, Russell Takeshi Shinohara, Christoph Berger, Sung Min Ha, Martin Rozycki, Marcel Prastawa, Esther Alberts, Jana Lipkova, John Freymann, Justin Kirby, and Michel Bilello. Identifying the best machine learning algorithms for brain tumor segmentation, progression assessment, and overall survival prediction in the brats challenge, 2019.
9. Weihao Weng and Xin Zhu. Inet: Convolutional networks for biomedical image segmentation. *IEEE Access*, 9:16591–16603, 2021.
10. Xiaojin Li, Wenhua Qian, Dan Xu, and Chunyu Liu. Image segmentation based on improved unet. *Journal of Physics: Conference Series*, 1815:012018, 02 2021.

11. Aryan Sagar Methil. Brain tumor detection using deep learning and image processing. In *2021 International Conference on Artificial Intelligence and Smart Systems (ICAIS)*, pages 100–108, 2021.
12. Ali Hatamizadeh, Yucheng Tang, Vishwesh Nath, Dong Yang, Andriy Myronenko, Bennett Landman, Holger R. Roth, and Daguang Xu. Unetr: Transformers for 3d medical image segmentation. In *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision (WACV)*, pages 574–584, January 2022.