

Comparative Analysis of Deep Learning Models on Brain Tumor Segmentation Datasets: BraTS 2015-2020 Datasets



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ABSTRACT

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Deep Learning neural networks have shown applicability in segmentation of brain tumor images. This research has been carried for comprehensive review of several deep learning neural networks. The datasets included in this study are standard datasets Multimodal Brain Tumor Segmentation (BraTS). This paper has summarized the performance of various deep learning neural network algorithms on BraTS datasets. Algorithms have been compared and summarized against the baseline models with specific attributes like dice score, PPV and sensitivity. It has been found that out of the different models applied on the BraTS 2015 dataset GAN in the year 2020 algorithm is showing better results on this data set. GAN architecture termed RescueNet gave the best segmentation results in terms of 0.94 dice score and 0.88 Sensitivity. This has been also observed that models used cascaded deep learning models had independent deep learning models at each stage which had no correlation among the stages which can cause class imbalance. Further it has been found that the Attention models tried to solve problem of class imbalance in the brain tumor segmentation task. This work also found that existing CNN's is having overfitting issues. For this ResNet models can add a rapid connect bounce relationship parallel to the layers of CNN to accomplish better outcomes for the brain tumor segmentation task.

1. INTRODUCTION

Diagnosis and later treatment plan for patients with brain tumor involves getting several MRI (Magnetic Resonance Imaging) scans of different modalities at different stages of life. These scans need to be assessed and evaluated by medical experts to see the growth in the region of interest and for further analysis. This assessment and evaluation process is cumbersome that's why there is a great need for automatic and accurate brain segmentation of image scans to help aid the medical experts. In the last few decades, this has been a challenging problem addressed by various researchers. Traditional machine learning models coupled with computer vision techniques were initially employed the segmentation reasonable but were not highly accurate. With the advent of Deep Learning (DL) models and high computational processing power, the segmentation problem can find solution which is giving hope to the field of medicine.

In the initial years, after 2012, Deep CNNs (Convolutional Neural Networks) were employed in various fields of medicine for different tasks in general and in medical image segmentation task in specific. Ronneberger's UNet [1] architecture became the base model for various image segmentation tasks. With the advent of generative models like Auto-encoders (AE) and Generative Adversarial Networks (GANs), researchers have tried to employ and adapt these models for medical image segmentation tasks to generate and

predict the segmentation pixels for the scans and it was seen that these models fared better to the initial DL models. Guided Attention models in recent years are also proving to enhance the segmentation accuracy results.

In the survey Multimodal Brain Segmentation Challenge (BRATS) have been considered to aim for improving brain tumor segmentation. Foremost researchers around the world participate in it and therefore this research have analyzed and compared these models' performance. Papers published in important journals like IEEE transactions in Medical Imaging, IEEE Access, Frontiers in Computational Neuroscience, Medical Image analysis, Scientific Reports and Neurocomputing which have used BRATS datasets have also been surveyed. Papers from major conferences like MICCAI, CVPR, ECCV, and NIPS were also examined which employed DL pipelines for Brain segmentation. Although there are some survey papers in literature, they have not included papers related to recent DL architectures. Lastly, some important techniques published as pre-printed versions on arXiv were also included as part of this study.

In a seminal work by Krihevsky et al. [2], potential of deep convolutional neural networks was demonstrated and thus started an era of application of deep neural networks for various applications almost replacing the traditional machine learning models. The author Kleesiek et al. discussed that deep learning models were used for various medical applications like skull stripping [3]. Deep learning methods are very much

usable for medical images [4-8]. The authors Singh et al. have presented review paper on deep learning in 3D medical images [9]. Deep learning is Specifically usable for brain segmentation for MRI images also [10-16]. Brain segmentation initially was done using deep CNNs later many other comes into light [17-20]. Ronneberger et al. [21] in their paper, came up with an architecture called UNet, which probably is still the most widely used model for medical image segmentation. It consists of a contracting path and an expansive path. It can be thought of as an encoder (downsampling) and then a decoder (upsampling). Several variations of UNet were then employed taking this architecture as the base model to improve the segmentation accuracy. Some of them were utilized for brain segmentation [22-25]. Few researchers have used 3D UNets [26, 27] for brain segmentation. Cascaded convolutional neural network architectures were used in [28, 29] for segmentation. With the advent of generative models, Auto encoders (AEs) were used to predict the segmentation pixels [30-33]. GANs which were generative models became popular in around 2018 found applications in brain segmentation [34-38]. Of late, attention modules in convolutional neural networks were found to give improved segmentation results [39-45]. Some recent papers focused not only on brain segmentation, but also on progression during the treatment phase and the survival prediction problem [46-52].

This survey gives important insights into the Deep Learning models developed and also includes a comparative study of the latest medical segmentation architectures for brain segmentation. In next section of the paper, DL models evaluated on the BraTS Dataset challenges. On basis of their performance on these Datasets identification of the best deep learning algorithm is done.

The rest of this paper is organized as follows: Section II introduces the datasets used in brain segmentation study. Section III illustrates the baseline deep learning architectures applied on different BRATS datasets. Section IV shows the segmentation accuracy obtained by these baselines methods with improved architectures. The conclusion of this paper and future works is discussed in Section V.

2. ANALYSIS OF MODELS EVALUATED

Multimodal Brain Image Segmentation (BraTS) challenge was started specifically to identify the state-of-the-art automated segmentation algorithms. This study is done by comparing various algorithms and to find which of these worked best on these challenge datasets. Brain segmentation has always been very challenging given the various kind of imaging modalities like T1 MRI, T1 contrast-enhanced MRI, T2 MRI, and T2 FLAIR MRI volumes. There is different type of primary or secondary to work with and the way in which the calls infiltrate the surrounding cells and progresses, it is hugely challenging task to segment it accurately even for medical experts. That is why even the segmentation labels are formed by taking the average of 3-4 ratings given by medical experts.

BraTS 2015 data set consists of about 300 High- Grade Gliomas (HGG) and Low- Grade Glioma (LGG) cases. The dataset consists of various MRI imaging modalities. Annotations comprises of the Whole (WT), the Core (TC), and the Gd-Enhanced Core (ET).

BraTS 2017 dataset though is greatly different from the BraTS 2015 dataset. Expert neuroradiologists have assessed 262 subjects of Glioblastoma Multiforme (GBM) and 199

subjects related to Low Grade Glioma (LGG) and labeled each scan as pre- or post-operative. Out of which, 135 GBM and 108 LGG cases were annotated by experts for the various glioma sub-regions and formed the training dataset for the experiments.

BraTS 2018 dataset also included T2 – weighted scans along with other imaging modalities. These scans were acquired under different clinical protocols and with various scanners from 19 different institutions.

BraTS 2020 dataset have been augmented with more scans acquired by 3T multimodal MRI machines, with accompanying ground truth labeled by expert board-certified neuroradiologists.

3. SEGMENTATION METHODS

After 2012, when the first deep learning model, AlexNet was proposed, a huge interest have come up in the field of deep learning. The deep model with its millions of parameters demonstrated tremendous computational power useful for various applications. As a result, in the last decade, brain segmentation results improved upto great extent.

3.1 CNN based methods

In initial papers, basic CNNs shown in Figure 1, were used for the segmentation purpose. Although the results were improvement over the traditional machine learning techniques, still the segmentation accuracy was not up to the mark especially for low grade s. Also, distinguishing between core and enhanced posed different challenge as the CNNs were not capable of giving context aware information. The Author Sille had used Dense hierarchical CNN for Brain Tumor Segmentation [53]. Later, some models were proposed which has a multiscale architecture for combining the segmentation maps at different resolutions.

Deep CNN model is also having applicability in Driver Drowsiness Detection [54]. Few others have tried having CNNs in parallel to fuse the segmentation maps. Still, there was a problem of class imbalance. To solve this, researchers have come up with multistage, cascaded CNNs. That led to some improvement but still each stage is independent and did not share parameters. As a result, the power of the architecture did not improve significantly.

Instead, it increased the complexity of the model, leading to huge number of parameters to be learned. Also, problems of over-fitting and vanishing gradients also appeared as a by-product of these models.

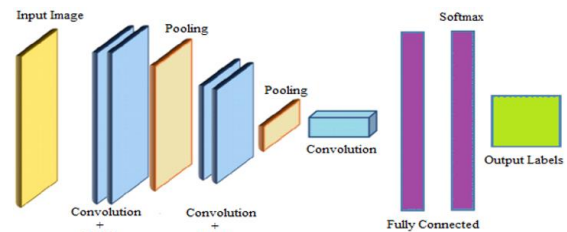


Figure 1. Basic CNN Architecture

3.2 U-Net based methods

A U-net architecture, introduced by Ronneberger et al. [21] shown in Figure 2, employed skip-architecture in a U-shaped

network to extract low level representations and high-level representations of the image simultaneously and then combined to produce a good resultant segmentation image. It was applied to biomedical images with a good degree of success. U-Net architecture has become extremely popular for its encoding-decoding model that still most of the models have it as a baseline for segmentation tasks.

Kamnitsas et al. [19] used U-Net based skip architecture to segment 220 HGG and 54 LGG cases belonging to BRATS 2015 dataset. The method achieved comparable results for core segmentation. Although enhanced segmentation on HGG yielded good results, those on LGG cases were not successful. Chen et al. [55] in their paper, proposed a hybrid pyramid U-Net architecture which provided a better framework for pixel level prediction of class labels. Global contextual information was integrated with region-based context information to produce improved segmentation results. Recently, in the study of Martini and Oermann [56], newer deep learning base models like ResNet [57], DenseNet [58] and NASNet were used as encoder/decoders in a U-Net like architecture for segmentation of brain lesions on FLAIR MRI image data. While in the study [59], a modified U-Net based architecture called DR-UNet 104 with 104 convolutional layers was proposed for brain lesion segmentation.

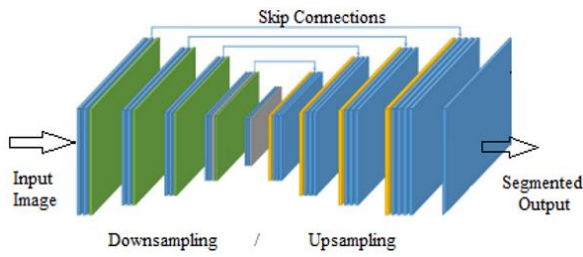


Figure 2. Baseline U-Net architecture

3.3 Autoencoders and generative adversarial networks (GANs)

Limitations of CNN based methods is the receptive fields of the convolutional filters. Because of the small receptive fields, it was seen that, they do not perform well in spatial congruity. In recent years, authors in papers [12, 13], have explored encoder-decoder models called auto-encoders shown in Figure 3, to model the data distribution of brain MRI of normal subjects and then used this knowledge to detect lesions on BRATS 2015 challenge dataset. In another paper [30], Baur et. al. employed a deep autoencoder model to process entire 2D brain slices instead of working on extracted patches. They have used a spatial Variational Autoencoder (VAE) network to encode the full contextual and structural information of the brain. It was shown as an improvement over the VAE models which fail to reconstruct accurate region due to bottlenecks.

Xue et al. [34], introduced a Generative Adversarial Network (GAN) shown in Figure 4, called SeGAN for brain segmentation. Unlike the classical GAN, the generator is a fully convolutional encoder-decoder architecture that predicts the pixels. They have shown that the GAN model performed better in comparison to the standard UNet segmentation architecture. Li et al. [38], have proposed a GAN model to enhance the spatial contiguity of the segmentation results and thereby improve the segmentation accuracy. The author Myronenko proposed an asymmetrical UNet with a large encoder for feature extraction and a small decoder for

reconstruction [33]. He also added a VAE branch to the model to improve the segmentation accuracy. It won the first place in BraTS 2018 challenge.

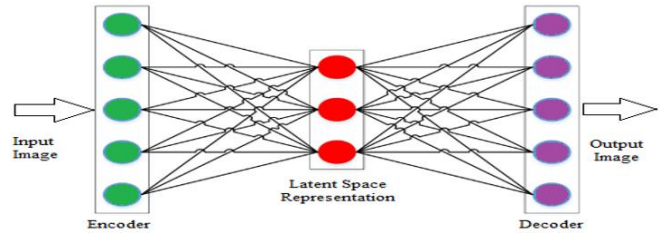


Figure 3. Auto-encoder architecture

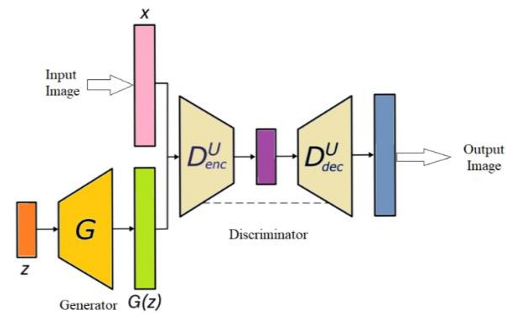


Figure 4. GAN architecture with UNet discriminator

In the study of Sun et al. [60], a 3D UNet segmentation network was integrated with a GAN architecture, called, parasitic GAN, which increased the segmentation accuracy while improving the generalization capability of the model as well. Rezaei et al. [61] proposed 3D conditional GAN (cGAN) which tried to solve the problem of class imbalance in the MR data. Nema et al. [36] introduced an unpaired 2D GAN architecture named RescueNet for brain segmentation. It overcame the need for paired data to be used during the training phase. Cirillo et al. [37] proposed a 3D GAN model, called Vox2Vox which segments the brain region voxel by voxel. The model suppresses the non- voxels simultaneously resulting in improved segmentation performance. The generator was built using UNet while the discriminator network used Patch GAN architecture. The Author Li et al. proposed a GAN architecture that could help in data augmentation named GAN [38]. This GAN architecture would help in improved training and thereby would result in increasing segmentation accuracy.

3.4 Attention mechanism

Attention mechanism was basically used to extract significant features and form these new refined feature maps appropriately. Attention module shown in Figure 5, had two stages, a channel attention and a spatial attention stage. This has led the researchers to achieve high segmentation results even with a 2D UNet baseline model compared to a 3D UNet model. It suppressed noise and insignificant features and increased the resolution of the feature maps. Also, it has lesser number of parameters compared to other models in use. Some researchers have integrated attention gates into skip connections of the UNet model while others tried to integrate into the decoder stage for improved feature maps. This helped in obtaining refined segmentation maps at various resolutions which were then combined in the final stage.

Channel attention stage can refine the feature maps channel wise, and the spatial attention stage improves the feature

response of the region-of-interest. In the brain segmentation task, this would mean the brain region.

Also, in some recent papers, attention modules were also integrated into the cascaded architectures to improve the results of feature maps after every stage. The feature maps at the end of each stage were refined and thereby produced improved segmentation output. Few have also integrated attention modules into auto-encoder and GAN architectures to enhance the results.

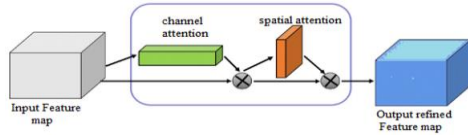


Figure 5. Attention module

4. COMPARISON AND DISCUSSION

Many deep learning models have been surveyed which are applicable in medical applications majorly brain segmentation. CNN, GANs and models integrated with attention modules were applied on BRATS datasets and their results are compared. Performance of various deep learning models have been presented for each BraTS dataset separately and their Comparative tables have been presented to help researchers for finding suitable model.

While evaluation parameters for BraTS 2015 dataset are Dice Similarity score, Positive Predictive Value (PPV) and

Sensitivity, for the other BraTS datasets, the evaluation parameters are slightly different. Apart from Dice similarity scores for segmentation, Hausdorff distance is taken as the dissimilarity measure between the output segmentation and the ground truth segmentation maps. If the output segmentation is highly accurate, then Hausdorff distance approaches zero and vice-versa.

Several models have been run and tested on the BraTS 2015 dataset shown in Table 1. Evaluation metrics were Dice score, PPV and Sensitivity. GAN architecture termed RescueNet proposed by Nema et al. [36] have given the best segmentation results in terms of dice score and Sensitivity. The algorithm achieved a high segmentation accuracy of 0.94 dice score and also a high sensitivity of 0.88 for whole. RescueNet is a generative model. The encoder-decoder architecture of the generator mimicked the baseline U-Net but is improved with additional residual skip-connections to resolve the vanishing gradient problem prevalent in deep learning models.

RescueNet also worked well on the BraTS 2017 dataset with impressive segmentation dice scores on whole, core and enhanced respectively Shown in Table 2. Another model proposed by Kong et al. [24] also performed well on the 2017 dataset. It used a hybrid pyramidal model with a baseline UNet architecture. Hybrid pyramidal UNet (HPU-Net) model had a UNet architecture with improvements in the decoder working.

The segmentation map was improved by extracting multi scale features during upsampling at different resolutions and then combining them pixelwise for a better segmentation. Regionwise contextual information was basically combined into global contextual information.

Table 1. State-of-art models employed on BraTS 2015 dataset

Year	Model	Paper	Dice Score			PPV			Sensitivity		
			WT	TC	ET	WT	TC	ET	WT	TC	ET
2016	CNN	Perriera et al. [62]	0.78	0.65	0.75	-	-	-	-	-	-
2017	UNet	Dong et al. [63]	0.86	0.86	0.65	-	-	-	-	-	-
	3D CNN + CRF	Kamnitsas et al. [64]	0.85	0.67	0.63	0.85	0.86	0.63	0.88	0.6	0.67
	DCNN	Hussain et al. [65]	0.86	0.87	0.9	-	-	-	0.86	0.86	0.94
2018		Chen et al. [25]	0.85	0.72	0.61	0.86	0.83	0.66	0.86	0.68	0.63
	Deep Recurrent Level Set	Le et al. [66]	0.88	0.82	0.73	-	-	-	0.91	0.76	0.78
	FCNN + CRF	Zhao et al. [67]	0.84	0.73	0.62	0.89	0.76	0.63	0.82	0.76	0.67
	Multi-Cascaded CNN + CRF	Hu et al. [68]	0.87	0.76	0.75	0.88	0.83	0.75	0.87	0.74	0.8
	GAN	Xue et al. [34]	0.85	0.7	0.66	0.92	0.8	0.69	0.8	0.65	0.62
2020	GAN	Nema et al. [36]	0.94	0.94	0.87	-	-	-	0.88	0.94	0.91
	Attention	Chen et al. [39]	0.84	0.72	0.63	-	-	-	-	-	-
	Attention	Zhou et al. [43]	0.87	0.75	0.65	0.89	0.85	0.63	0.88	0.73	0.7

Table 2. State-of-art models employed on BraTS 2017 dataset

Year	Model	Paper	Dice Score			Hausdorff Distance		
			WT	TC	ET	WT	TC	ET
2017	3D FCNN	Jesson and Arbel [69]	0.88	0.78	0.68	6.58	7.11	8.11
		Isensee et al. [49]	0.89	0.82	0.70	6.04	6.95	6.24
	3D CNN + CRF	Kamnitsas et al. [64]	0.90	0.79	0.73	4.23	6.56	4.50
	CNN	Wang et al. [70]	0.90	0.83	0.78	3.89	6.47	3.28
	CNN	Pereira et al. [62]	0.86	0.76	0.69	8.48	10.51	6.13
2018	Hybrid Pyramid UNet	Kong et al. [24]	0.92	0.80	0.76	-	-	-
	DCNN	Shaikh et al. [22]	0.83	0.65	0.65	-	-	-
	PixelNet	Islam and Ren [71]	0.85	0.70	0.62	11.96	30.11	57.45
		Mostefa et al. [72]	0.89	0.76	0.81	14.62	17.40	12.94
2020	Attention	Noori et al. [73]	0.79	0.88	0.78	-	-	-
	RescueNet (GAN)	Nema et al. [36]	0.94	0.85	0.93	-	-	-
	Attention	Zhang et al. [40]	0.88	0.78	0.75	-	-	-
	Attention	Zhou et al. [43]	0.90	0.84	0.78	4.38	7.56	3.29
	Attention + Context Constraint	Zhou et al. [45]	0.89	0.81	0.73	5.73	6.79	7.68

Table 3. State-of-art models employed on BraTS 2018 dataset

Year	Model	Paper	Dice Score			Hausdorff Distance		
			WT	TC	ET	WT	TC	ET
2018	nn-Unet	Isensee et al. [74]	0.90	0.85	0.80	5.23	7.23	2.81
	Cascade CNN	Wang et al. [75]	0.87	0.78	0.75	5.90	8.03	4.53
	3D CNN	Chandra et al. [76]	0.87	0.79	0.74	5.03	9.58	5.57
	2-stage FCNN	Marcinkiewicz et al. [29]	0.86	0.76	0.72	-	-	-
	Auto Encoder	Myronenko [33]	0.91	0.86	0.82	4.51	6.85	3.92
	Attention guided 2D UNet	Noori et al. [73]	0.89	0.82	0.81	4.05	6.34	2.93
2019	Attention Gate ResU-Net	Zhang et al. [40]	0.87	0.81	0.77	5.62	8.36	3.57
	Multicascade CNN + CRF	Hu et al. [68]	0.88	0.75	0.71	12.60	9.62	5.68
2020		Estienne et al. [77]	0.88	0.69	0.71	7.7	11.1	5.8
	Guided Attention	Zhou et al. [43]	0.90	0.85	0.81	4.88	6.93	2.88

Table 4. State-of-art models employed on BraTS 2020 dataset

Year	Model	Paper	Dice Score			Hausdorff Distance (mm)		
			WT	TC	ET	WT	TC	ET
2020	DR-UNet	Colman et al. [78]	0.86	0.80	0.75	10.41	21.84	24.68
	nn-UNet	Isensee et al. [74]	0.89	0.85	0.82	8.49	17.33	17.80
	3D GAN	Cirillo et al. [37]	0.87	0.81	0.78	6.44	24.36	18.95
	Attention	Lyu and Shu [42]	0.87	0.83	0.82	11.43	19.97	15.67
	Attention	Liu et al. [44]	0.87	0.82	0.77	6.45	20.23	27.17

Algorithms which worked well on BraTS 2018 dataset were a nn-UNet model proposed by Isensee et al. [74], an auto-encoder model proposed by Myronenko et al. [33], and a guided attention model proposed by Zhou et al. [43].

nn-UNet model had a 3D UNet architecture as a baseline with encoder –decoder, connected by skip connections. Loss function in this model was framed as sum of Dice and cross-entropy loss. The error function tries to minimize the segmentation error on edem, necrosis and enhancing regions. The model used Stochastic Gradient Descent (SGD) with Nestorov momentum of 0.99 to escape the local minima’s in the loss landscape. It also used leaky ReLU’s as activation functions for neurons to introduce non-linearities into the network.

In Myronenko’s paper [33], a variation of the baseline UNet, termed the assymetrel UNet had an architecture consisting of a large encoder for feature extraction (downsampling) and a small decoder (upsampling) for reconstruction. The model also had a Variational Auto encoder branch to the model to improve the segmentation accuracy. It won the first place in BraTS 2018 challenge. Model proposed by Zhou et al. [43] utilized a guided attention model to improve the segmentation result. It won the third place on BraTS 2018 challenge competition. Results shown in Table 3. The model fared exceptionally well on 2020 dataset as well. The model tried to improvise on solving the problem of class imbalance in the brain segmentation task. Earlier models used cascaded deep learning models to deal with this problem but the cascaded model had independent deep learning models at each stage which had no correlation among the stages. In this model though, the parameters among the deep learning model were shared and there was feedback from one model to another which reduced the gap/problem attributed to multi stage CNNs to solve class imbalance. Also, it is a light weight deep learning model. It gave impressive segmentation results shown in Table 4.

5. CONCLUSION AND FUTURE WORK

Automatic and accurate Brain Segmentation has been a

challenge since many years. Deep Learning methods helped in this field to a major extent. This Paper has presented review of the state-of-the-art deep learning models which showed impressive performance on standard datasets like BraTS datasets for brain tumor segmentation.

This has been find that out of the different models applied on the BraTS 2015 dataset GAN in the year 2020 algorithm is showing better results on this data set. GAN architecture termed RescueNet gave the best segmentation results in terms of dice score and Sensitivity. The algorithm achieved a high segmentation accuracy of 0.94 dice score and also a high sensitivity of 0.88 for the whole tumor. Further it has been found that RescueNet also worked well on the BraTS 2017 dataset with impressive segmentation dice scores on whole tumor, tumor core and enhanced tumor respectively. This has been observed that models used cascaded deep learning models to deal with this problem but the problem found is that cascaded model had independent deep learning models at each stage which had no correlation among the stages which can cause class imbalance. It’s also analysed that, Attention models tried to improvise on solving the problem of class imbalance in the brain tumor segmentation task in this model though sharing parameters via feedback from one model to another which reduced the problem attributed to multi stage CNNs to solve class imbalance on BraTS 2020 datasets. Reseracher can take benefits these results and can decide the appropriate model for their work requirements.

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