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Deep learning project on medical image segmentation of brain tumor.

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1 Introduction

Brain tumours are collections of aberrant cells in the human brain that can impair neighbouring healthy brain tissues and the nervous system. One of the most crucial organs for coordinating the many elements of the human body is the brain. Brain tumours, which are regarded as one of the most deadly disorders in humans, can disrupt the brain's general functionality. Thus, early detection of brain tumors is essential for prompt and effective therapy. The human brain may be afflicted by multiple types of tumors, including gliomas, meningiomas, and pituitary tumors.

1.1 Scope of the document

Convolutional neural networks (CNN), which automatically learn the high dimensional hierarchical features, are the most prominent computer vision approach. Contrarily, traditional machine learning algorithms rely on manually created feature engineering. In order to make the training process faster and more reliable, a deep residual convolutional neural network and U-Net network termed dResU-Net are combined in this study to provide a novel strategy for segmenting the brain tumour sub-regions. The dResU-Net network, a modified version of the U-Net, has two parallel pathways called encoder and decoder. In the proposed model, the encoder portion of the U-Net network makes use of residual convolutional blocks.

The main goal of using these blocks in the encoder component is to take advantage of both low-level and high-level characteristics by utilising the skip connections for segmentation mask prediction.

1.2 Motivation

Brain tumours can now be swiftly and precisely identified by neuro-oncologists with the use of computer-aided diagnostic (CAD) technologies. MRIs are a useful technique that offer precise images of the body's tissues and organs. The most precise tool for locating and measuring brain tumours is still MRI (Wulandari, Sigit, Bachtiar, 2018). Multidimensional data from MRIs can be accurately analysed to assist localise, track, and direct treatment of disease.

In the domain of healthcare imaging, machine learning has been utilised for disease diagnosis, prediction, categorization, and image segmentation. The majority of current research in this area has focused on the segmentation and classification of tumours such lung and colon cancers (Debelee et al., 2017, Kebede et al., 2020, Yu et al., 2022), brain tumours (Gab Allah et al., 2021), and breast cancer (Debelee, Kebede, Schwenker, Shewarega, 2020).

The majority of brain tumour image analysis in clinical practise nowadays is done by hand. This takes a lot of time and is prone to human mistake, especially if not done by a disease specialist. For successful cancer research, it is essential to segment healthy and pathologic brain tissue in MRIs, including the determination of subregions, in order to analyse brain tumours and choose treatment options (Bauer, Nolte, Reyes, 2011). According to, segmenting brain tumour MRIs is crucial for improving tumour diagnosis and treatment.

2 Literature Survey

2.1 Paper 1

Author–Cao, Y., Zhou, W., Zang, M., An, D., Feng, Y., Yu, B.
Title– "MBANet: A 3D convolutional neural network with multi-branch attention for brain tumor segmentation from MRI images. Biomedical Signal Processing and Control, 80, 104296."
Method/ approach used– The 3D convolutional neural network with 3D multi-branch attention called MBANet is proposed in the paper. First, the basic unit (BU) module of MBANet is constructed using the optimised shuffle unit. The BU module uses channel shuffle to jumble the convolutional channels after fusion and group convolution to execute convolution after the input channel has been split. The attention layer of the encoder is then used by MBANet's novel multi-branch 3D Shuffle Attention (SA) module. The 3D SA module separates the feature maps into small features and groups along the channel dimension. The 3D SA module adopts the BU module and builds channel attention and spatial attention for each small feature.
Achieved Performance – Experiments on the BraTS 2018 and BraTS 2019 show that the dice of ET, WT and TC reach 80.18percent, 89.80percent, 85.47percent and 78.21percent, 89.79percent, 83.04percent, respectively.
Disadvantages– It has been demonstrated through a number of trials that MBANet offers good segmentation performance as well as some stability against noise and blurring. Yet MBANet also includes some restrictions: MBANet solely uses publicly available multimodal datasets for its experiments.
Advantages– Most of the better methods are outperformed by MBANet. MBANet applies the 3D SA module attention layer to the feature maps on each channel after using the BU module as a baseline. Given that the brain tumour region is smaller than the overall MRI picture, increasing the focus can significantly enhance the segmentation outcomes.
Dataset
BraTS 2018 and BraTS 2019 validation datasets
scope–MBANet exclusively experiments with multimodal public datasets. As a result, more data is required, and collaboration with the hospital to acquire more clinical data will be beneficial. Hence, in the future, employ clinical data to truly apply it to medical clinical research.
Year2023

2.2 Paper 2

Author– Bruno Machado Pacheco , Guilherme de Souza e Cassia b, Danilo Silva c
Title– Towards fully automated deep-learning-based brain tumor segmentation: Is brain extraction still necessary?
Approach– Deep learning models applied to multi-modal MRIs. Currently, these models are trained on images after a preprocessing stage that involves registration, interpolation, brain extraction (BE, also known as skull-stripping) and manual correction by an expert.
Performance – Experiments show that the choice of a BE method can compromise up to 15.7
Disadvantages we propose training and testing tumor segmentation models on non-skull-stripped images, effectively discarding the BE step from the pipeline. Our results show that this approach leads to a competitive performance at a fraction of the time.
Advantages– We conclude that, in contrast to the current paradigm, training tumor segmentation models on non-skull-stripped images can be the best option when high performance in clinical practice is desired.
Dataset– BraTS 2020
Year– 2023

2.3 Paper 3

Author– Ajay S. Ladkat, Sunil L. Bangare, Vishal Jagota, Sumaya Sanober, Shehab Mohamed Beram, Kantilal Rane, Bhupesh Kumar Singh
Title– ”Deep Neural Network-Based Novel Mathematical Model for 3D Brain Tumor Segmentation”, Computational Intelligence and Neuroscience
Method/ approach used– In the work,a completely automated brain tumor segmentation method based on a mathematical model and deep neural networks (DNNs) was provided. Each slice of the 3D picture is enhanced by the suggested mathematical model, which is then sent through the 3D attention U-Net to provide a tumor segmented output. The study includes a detailed mathematical model for tumor pixel enhancement as well as a 3D attention U-Net to appropriately separate the pixels
Achieved Performance – The suggested system architecture for segmentation has accuracy, precision, recall, and F1 score of 99.90percent, 99.90percent, 98.5percent, and 98.50percent, respectively
Disadvantages– The added dimension of 3D structures complicates understanding the model’s findings in order to develop predictions. Medical specialists are hesitant to believe CNN projections because of their lack of explainability and black-box nature
Advantages– The suggested model beats the 3D attentive U-Net and the 3D digital U-Net paradigm across all areas, including ET, WT, an Turn on screen reader support To enable screen reader support, press Ctrl+Alt+Z To learn about keyboard shortcuts, press Ctrl+slash3 collaborators have joined the document.
Dataset

All of the tests in the paper are done with BraTS 2019.
scope–The proposed system approach will be incredibly useful in extracting volume of the tumor.
Year–2022

2.4 Paper 4

Author–Jiangyun Li, Hong Yu, Chen Chen, Meng Ding, Sen Zha
Title– Category Guided Attention Network for Brain Tumor Segmentation in MRI
Method/ approach used– Magnetic resonance imaging (MRI) has been widely used for the analysis and diagnosis of brain diseases. Accurate and automatic brain tumor segmentation is of paramount importance for radiation treatment. However, low tissue contrast in tumor regions makes it a challenging task.
Achieved Performance – Experimental results on the BraTS 2019 datasets show that the proposed method outperformers the state-of-the-art algorithms in both segmentation performance and computational complexity
Disadvantages– There may be some possible limitations in this study. Since we update the feature map based on the category, the computational complexity may expand as the number of categories increases.
Advantages– The experimental results on BraTS 2019 dataset show that our approach is highly effective. The final dice scores (78.83percent, 89.29 percent, 82.32 percent for ET, WT and TC, respectively) are superior or comparable to that of the state-of-the-art methods.
Dataset
BraTS 2019 dataset
scope–There may be some possible limitations in this study. Since we update the feature map based on the category, the computational complexity may expand as the number of categories increases. This work may consider dataset with larger number of categories and conduct more detailed intra-class update experiments. The future work can also include sensitivity analysis on the number of categories. In addition, this work may consider more datasets such as the decathlon challenge to verify the generalization of the method
Year–2021

2.5 Paper 5

Author– Rehan Raza a b, Usama Ijaz Bajwa a, Yasar Mehmood a, Muhammad Waqas Anwar a, M. Hassan Jamal a
Title– 3D deep residual U-Net based brain tumor segmentation from multimodal MRI
Approach– This research paper presents an end-to-end framework for automatic 3D Brain Tumor Segmentation (BTS). The proposed model is a hybrid of the deep residual network and U-Net model (dResU-Net). The residual network is used as an encoder in

the proposed architecture with the decoder of the U-Net model to handle the issue of vanishing gradient. The proposed model is designed to take advantage from low-level and high-level features simultaneously for making the prediction. In addition, shortcut connections are employed between residual network to preserve low-level features at each level.
Performance – The proposed dResU-Net was trained and validated on the BraTS 2020 training dataset as the ground truth for the validation data is not available. Therefore, the model is trained on 80 percent data, validated on 10 percent, and tested on 10 percent of the total data. The trained model has been utilized to segment the test images of brain tumors. The proposed method generates a 3D volume of the segmentation mask, which includes tumor regions WT, ET, and TC.
Disadvantages The performance of the proposed method can be improved by different kinds of augmentation techniques or by using a large benchmark dataset. Furthermore, the size of the dataset can also be increased by using synthetic data generation augmentation techniques.
Advantages– The proposed model successfully embedded the residual blocks with identity mapping in the encoder part of the U-Net model to improve the learning process by preserving the local feature response and passing it through the activation from the appropriate level of the encoder side to the decoder side by using skip connections.
Dataset– The model was trained and validated on the BraTS 2020 training dataset.
Scope– More 3D-based architectures should be explored which keep computational cost in consideration while utilizing the maximum possible contextual information. Moreover, the performance of selected systems can be improved by removing false positive rates using post-processing techniques. In addition, this work can be extended to clinically challenged medical imaging problems and other segmentation applications i.e., Liver tumor segmentation and Kidney tumor segmentation problems, etc.
Year– 2023

2.6 Paper 6

Author– Yankang Chang a, Zhouzhou Zheng b, Yingwei Sun a, Mengmeng Zhao a, Yao Lu a, Yan Zhang
Title– DPAFNet: A Residual Dual-Path Attention-Fusion Convolutional Neural Network for Multimodal Brain Tumor Segmentation
Approach– In DPAFNet, the dual path convolution is applied to broaden the network scale and residual connection is introduced to avoid network degradation. An attention fusion module is proposed to aggregate channel level global and local information, in which feature maps of different scales are fused to obtain features that are enriched in semantic information. This makes the object information of small tumors get full attention.
Performance – The proposed DPAFNet achieves Dice score of 79.5, 90.0 and 83.9 percent in the enhancing tumor, whole tumor and tumor core on BraTS2018, respectively. On BraTS2019, it achieves Dice score of 78.2, 89.0 and 81.2 percent in the enhancing

tumor, whole tumor and tumor core, respectively.
Disadvantages When the value of dilation rate is large, the grid effect will appear when extracting features, which will lose the continuity of context information and reduce the segmentation effect of pixel level tasks.
Advantages– An efficient 3D model (DPAFNet) for brain tumor segmentation based on dual-path (DP) module and multi-scale attention fusion (MAF) module is proposed. A novel 3D feature extraction block consisting of DP module and MAF module is proposed. The MAF module is used to aggregate global and local information on channel level. A 3D IDCM module which is beneficial to dense pixel-level prediction is introduced to merge feature maps with different receptive fields.
Dataset–

BraTS2018, BraTS2019 and BraTS2020 datasets

Scope– "The future work could be exploring the application of self-attention in 3D brain tumor MRI images, and further build the transformer model in the encoder to obtain richer information for brain tumor segmentation. "
Year– 2023

3 Gaps in research

There may be some possible limitations in these studies. Since the feature map is updated based on the category, the computational complexity may expand as the number of categories increases. This work has not considered dataset with larger number of categories and conducted less detailed intra-class update experiments. These works also doesn't include sensitivity analysis on the number of categories. Also some datasets such as the decathlon challenge used to verify the generalization of the method have not been considered.

4 Problem Statement

To develop a deep learning model to perform fully automatic brain tumor segmentation on MRI scans.

MRI scans can be obtained in a variety of machines using a variety of acquisition parameters and techniques. As a result, the identical tumorous cells appear very differently in photos taken at other hospitals. Tumor segmentation algorithms must be robust to this variation since they will be used to analyse data from multiple institutions.

However, low tissue contrast in tumor regions makes it a challenging task. So our motive is to enhance the accuracy of such image segmentation.

5 Proposed solution

5.1 Methodology Proposed

We suggest the Category Guided Attention U-Net, a brand-new segmentation network (CGA U-Net). We create a Supervised Attention Module (SAM) based on the attention mechanism in this model, which can capture more information.

feature maps with accurate and consistent long-range dependencies without adding a lot of computational effort. Additionally, by combining pixels from the same category, we present an intra-class updating strategy to reconstruct feature maps.

Model used

U-Net with the encoder-decoder structure to generate a dense prediction of the entire image. After that, a variety of U-Net variants based on the encoder-decoder architecture have emerged in an endless stream, and have achieved convincing results . For brain tumor segmentation task, the state-ofthe-art methods are based on the 3D U-Net CGA U-Net can effectively capture the global semantic information in the MRI image by using the SAM module, while significantly reducing the computational cost.

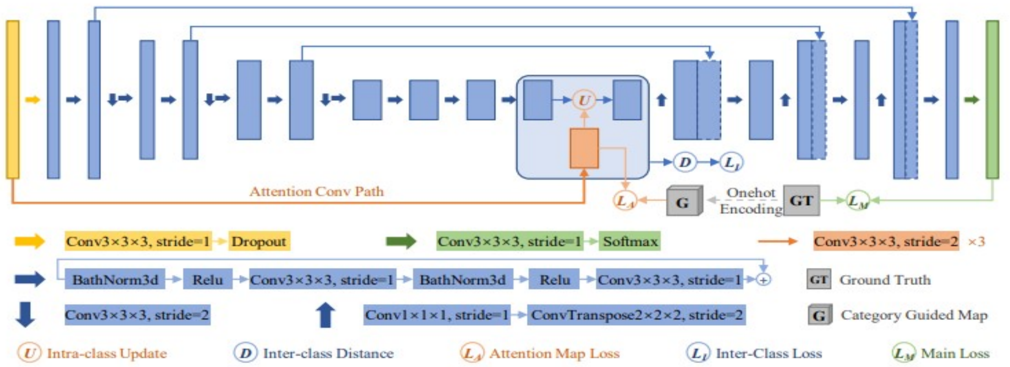

figure above denoting the Overview of the proposed category guided attention U-Net (CGA U-Net).

Dataset used-

Here we have used BraTS 2020 dataset. All BraTS multimodal scans are available as NIfTI files (.nii.gz) and describe a) native (T1) and b) post-contrast T1-weighted (T1Gd), c) T2-weighted (T2), and d) T2 Fluid Attenuated Inversion Recovery (T2-FLAIR) volumes, and were acquired with different clinical protocols and various scanners from multiple (n=19) institutions, mentioned as data contributors here

5.2 Expected outcomes

We display the segmentation data obtained using several techniques. In the visualisation experiment, it should be highlighted that we choose 80 percent of the data for training and the remaining 20 percent for testing and visualisation. Our technique is particularly effective in filling in lacking tumour features and controlling over-segmentation because it can capture steady and precise global context information.

Certain severe scenarios with low ET scores are avoided since our method partially inhibits over- and under-segmentation. As a result, our approach performs better in terms of standard deviation, which increases the system's stability in the face of actual complex situations.

5.3 Challenges

Challenges were faced during dataset finding, feature selection , model preparation and finally converting it to federated model

Modern techniques for a brain tumour segmentation challenge are based on the 3D U-Net , a 3D encoder–decoder architecture with skip connections. Yet, because of the challenges in establishing connections between long-distance voxels,and due to the tiny convolution kernel size. Similar to long-distance dependence, we try to extract global semantic information from medical pictures, which describes the relationship between any two locations in the image or matrix without taking into account their physical proximity. The convolution kernel's restriction, however, makes it challenging to learn global semantic data that can successfully direct the model to segment. Oversegmentation or under-segmentation will also be inhibited when building links between distant pixels.

CPNet introduces a context prior (CP) layer based on the attention mechanism, which contains a CP map similar to attention map. The CP map depicts the relationship between any two points in the image, however the channel dimension, which makes up the first dimension of the CP map, does not accurately depict the relationship between one point and other points (spatial dimensions). This could make parameter optimization challenging. Conflicts between the affinity loss used to supervise CP map and the loss for class label prediction in back propagation will also arise when CP map is obtained straight from local feature map using a convolution since they share the parameters prior to local feature map.

6 Dataset Description

The Dataset selected is Brain Tumor Segmentation(BraTS2020).

All BraTS multimodal scans are available as NIfTI files (.nii.gz) and describe a) native (T1) and b) post-contrast T1-weighted (T1Gd), c) T2-weighted (T2), and d) T2 Fluid Attenuated Inversion Recovery (T2-FLAIR) volumes, and were acquired with different clinical protocols and various scanners from multiple (n=19) institutions, mentioned as data contributors here.

6.1 Tools and Libraries used

python 3.7
pytorch 1.6.0
torchvision 0.7.0
pickle
nibabel

7 Conclusion

Deep learning is the best method to do medical image segmentation with the great accuracy For the purpose of automatically segmenting brain tumour using MRI, we have suggested a novel architecture called CGA U-Net. The SAM significantly improved the segmentation results with only 0.095M parameters and around 0.675G FLOPs. To reconstruct the feature map accurately and efficiently, we designed intra-class update method and inter-class distance optimization. The experimental results on BraTS 2019 dataset show that our approach is highly effective. The final dice scores (78.83, 89.29, 82.32percentfor ET, WT and TC, respectively) are superior or comparable to that of the state-of-the-art methods.

7.1 Future scope

This study may have some potential shortcomings. Since we update the feature map based on the category, the computational complexity may expand as the number of categories increases. This work may consider dataset with larger number of categories and conduct more detailed intra-class update experiments. The future work can also include sensitivity analysis on the number of categories. In addition, this work may consider more datasets such as the decathlon challenge to verify the generalization of the method.

8 References

1. Ajay S. Ladkat, Sunil L. Bangare, Vishal Jagota, Sumaya Sanober, Shehab Mohamed Beram, Kantilal Rane, Bhupesh Kumar Singh "Deep Neural Network-Based Novel Mathematical Model for 3D Brain Tumor Segmentation", Computational Intelligence and Neuroscience, vol. 2022, Article ID 4271711, 8 pages, 2022. https://doi.org/10.1155/2022/4271711

2. Cao, Y., Zhou, W., Zang, M., An, D., Feng, Y., Yu, B. MBANet: A 3D convolutional neural network with multi-branch attention for brain tumor segmentation from MRI images. Biomedical Signal Processing and Control, 80, 104296. https://doi.org/10.1016/j.bspc.2022.104296

3. 3D deep residual U-Net based brain tumor segmentation from multimodal MRI

4. Yankang Chang a, Zhouzhou Zheng b, Yingwei Sun a, Mengmeng Zhao a, Yao Lu a, Yan Zhang DPAFNet: A Residual Dual-Path Attention-Fusion Convolutional Neural Network for Multimodal Brain Tumor Segmentation