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# Detection of brain tumours using U- Net Based Architectures

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**Abstract**.

Brain tumours are unwanted masses of abnormally grown cells in the human brain. Originate in the brain, which would be primary brain tumours, or migrate from other parts of the body, which would be secondary (metastatic) brain tumours. There are different types of brain tumours such as noncancerous (benign) and cancerous (metastatic) ones. In the era of medical image processing and health technology to perform early detection and estimation of such primary or secondary tumours image segmentation models are much popular. In this paper/work the previous traditional models are replaced with new machine learning and deep learning techniques. The proposed U-Net-based architectures are prevalent marked a trend in the tumour detections. A new module is proposed as DCA with skip connections such as U-Net and its variants with 3D models like pre-trained models with capability of highest degree of integration into any encoder-decoder architectures its performance is intended. The overall performance of 3D net models not only limited to the images of medical image processing but also for electrochemical sensors, nano, and micro-chip level material-layer deposition areas too.

**Keywords:** Maximum 4 keywords. U-Net models; Pretrained MobileNetV2; Image segmentation; Brain tumours, Skip connect Algorithms

## 1. Introduction

Brain tumours are masses of abnormally growing cells in the brain. They can originate in the brain, which would be primary brain tumours, or migrate from other parts of the body, which would be secondary (metastatic) brain tumours [1]. There are different types of brain tumours such as noncancerous (benign) and cancerous (metastatic) ones. Currently, in the United States alone, 7 lakhs of people live with primary brain tumours, and more than 85-90 thousands of people were diagnosed in 2021-2022.which shows that survival rate of a year

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among patient's ages 55–64 is 45%, while for patients ages 65–75, it is only 30%. In addition, an early diagnosis of tumours also plays vital role in the survival rate [2].

Recently, automated brain tumour detection models become much popular and accurate and helpful with the continued development of ML and DL adopted to reduce the cost of brain tumour detection technology and make it available to common people where primary pre on-time detection with improving survival rate is the ultimate goal. The present work introduce a DCA module that can be integrating it into six U-Net-based architectures such as U-Net, V-Net, R2Unet, ResUnet++, Double U-net and MultiResUnet [3]

## 2. Methods

Development of accurate and reliable tumour segmentation from multi-modal MRI remains a challenging task due to many sources of variability, including: tumour types, shapes and sizes, intensity and contrast difference in MR images, etc [4]. Multi-modality magnetic resonance imaging (MRI) images are applied to segment specific lesion areas of the brain tumour. Single-modality data do not take full advantage of modality classical approaches include multi atlas segmentation, probabilistic graphical models like Markov Random Field (MRF) [6] and Conditional Random Field (CRF), Random Forest (RF) [5].

The idea of path aggregation has important guiding significance for brain tumour segmentation. Here three main problems. (1) Excessive noises are introduced in multiple up sampling processes with deep structure. (2) The capacity of the decoder is insufficient. (3) The feature pyramid up sampling process needs too much graphic memory resources. In this paper, a path aggregation U-Net (PAU-Net) model is proposed to improve the brain tumour segmentation performance. These three problems above have been mitigated by using the following three structures [6]

In this paper, a path aggregation U-Net for brain tumour segmentation with aggregation encoder facilitates the dissemination of deep information, shortening the distance between deep layers and the output layer in the network. Furthermore, an enhanced decoder is proposed to employ more channels corresponding to the accommodation requirements. Then, an efficient feature pyramid is proposed to use a small number of memory resources to connect multi-level features and output the segmentation results.

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In this work shorten the distance between output layers and deep features by bottom-up path aggregation encoder (PA), reducing the introduction of noises. experiments in BraTS2017 and BraTS2018 datasets are performed [7].

These have been successfully used for the task of tumour segmentation. Methods based on generative models have also been explored [8] for tumour segmentation. Inspired by the success of deep learning in many tasks related to natural images like semantic segmentation [10], object detection [11], and classification [12], many deep learning based approaches have been proposed for various tasks in medical images like segmentation [13], synthesis [14], and classification [15]. Various CNN architectures have been explored for brain tumour segmentation

In this work, 3D brain image data and created a new architecture based on a 3D U-Net model that uses multiple skip connections with cost-efficient pretrained 3D MobileNetV2 blocks and attention modules. These pretrained MobileNetV2 blocks assist the architecture by providing smaller parameters to maintain operable model size in terms of computational capability and help the model to converge faster. Skip connections play an important role as they are responsible for passing extracted features to the decoder block from the encoder block to detect the tumour.

In recent BraTS challenges [11], deep learning based approaches have outperformed classical methods. In this work develop a modified version of the popular 3D U-net [13] architecture for brain tumour segmentation task on BraTS 2018 datasets is developed. In this paper, the 3D U-net is trained using Categorical Cross Entropy (CCE) loss function on BraTS 2018 training dataset and a curriculum on class weights is employed to address class.

*a. U-NET Model Architecture*

For the purpose of performing biomedical image segmentation tasks, a deep learning model architecture known as the U-Net architecture was developed. Since then, it has been implemented successfully in a variety of other spheres as well. The U-shaped design of this architecture is one of its defining characteristics, and it has had a significant impact on the field of computer vision.

For jobs that demand high-resolution output maps, such as segmenting objects or regions of interest in images, the U-Net design has proven to be quite effective. One example of this is the task of segmenting. Its architecture permits the maintenance of spatial information and

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the incorporation of both local and global characteristics, which enables it to perform a variety of image-to-image translation jobs with relative ease.

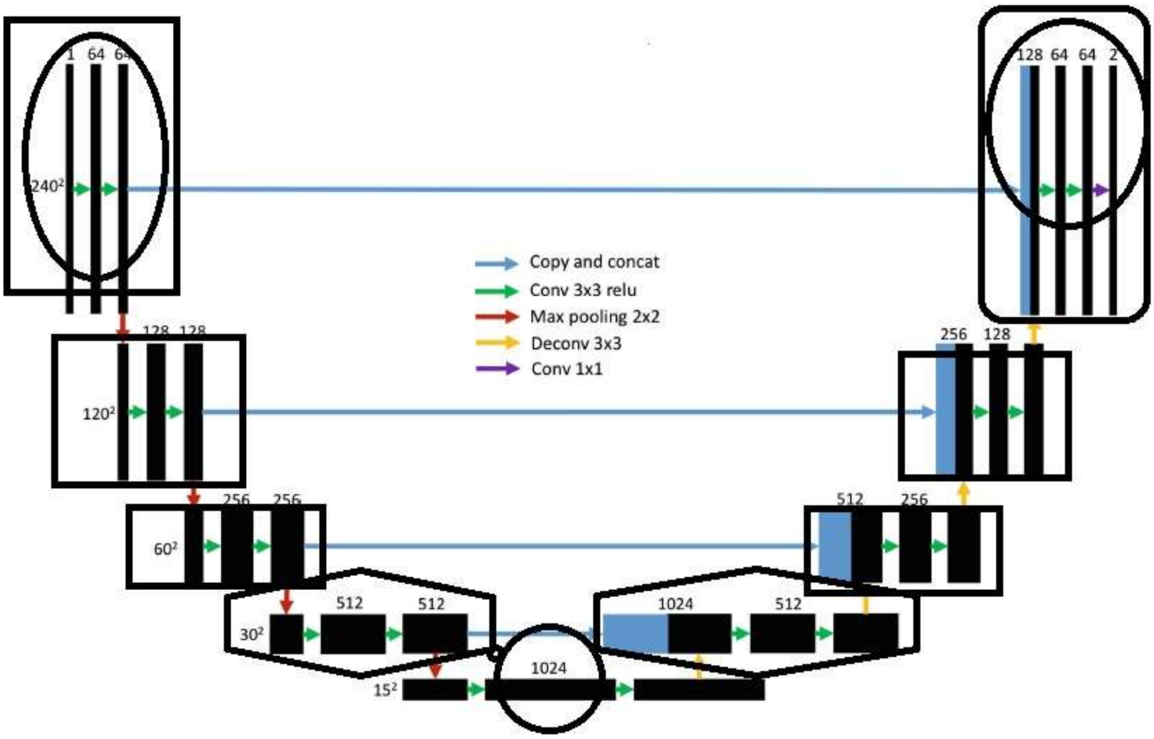


**Figure 1** U-Net architecture frame works

## 3. Results and Discussion

All of the programs developed for this study were built in Python with a Keras backend utilizing Tensor Flow, and they all ran on a single PC equipped with a GTX 1080ti GPU. Out of 335 T1W-MRI labelled training subjects, 166 participants are unlabeled for the final exam, and 125 are unlabeled for validation. Brain tumors and T1-weighted images are extracted from each of the 256 x 256 images in the BraTs 2019 dataset.

We used a two-stage, 100-epoch patching procedure to train the network, utilizing the saved model from the first stage as the foundation for the second. When using an Adam optimizer with a starting offset of 4, a patch overlap of 32, and a learning rate of 5e-4, the optimizer would experience a 50% decrease in its learning rate after 10 steps in which the loss value remained unchanged.

Common metrics used in image segmentation and object detection tasks to evaluate the accuracy and quality of segmentation results include the Dice coefficient (also known as the

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Srensen-Dice coefficient), the Jaccard index (also known as the Intersection over Union or IoU), and the Hausdorff distance.

In the process of analyzing medical images, the segmentation of brain tumors plays an essential function. In this research, the performance of U-Net, Attention (ATT) models, and Recurrent Residual (R2) U-Net architectures for brain tumour segmentation is examined by utilizing similarity and distance measures. Each of these architectural designs comes with its own unique set of benefits and qualities. The architecture of U-Net is in the shape of a U, with an encoder located on the left and a decoder located on the right. The spatial information and characteristics are recorded by the encoder, while the spatial resolution is reconstructed by the decoder.

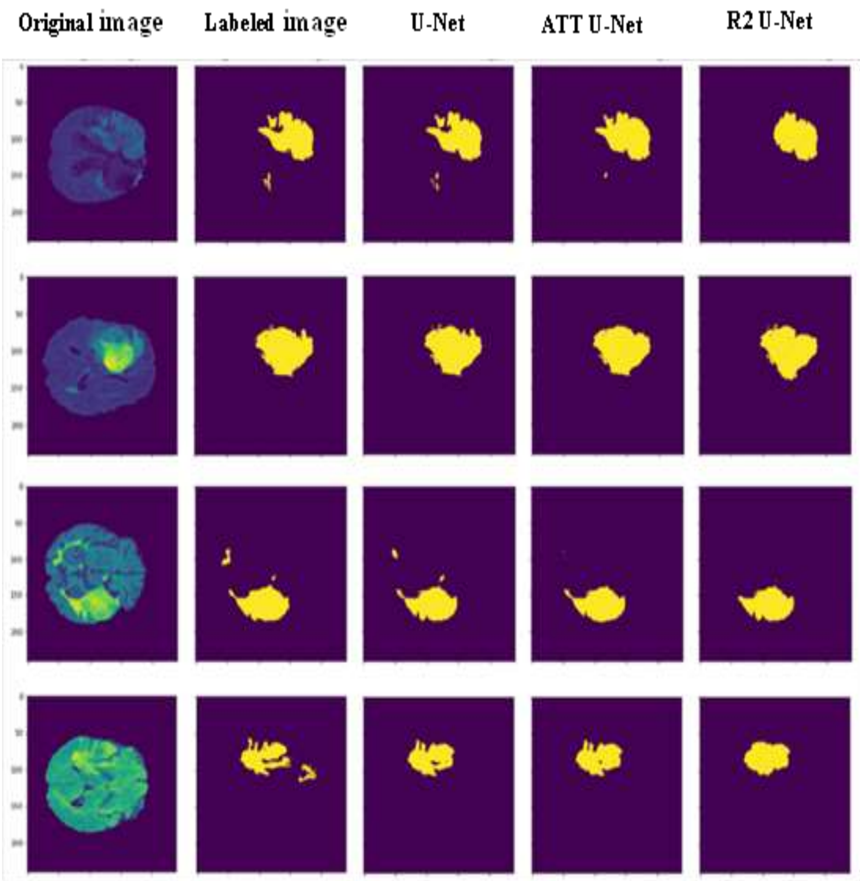


**Figure 1** Segmentation results of various models.

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**Table 1** The accuracy of various datasets

| S. No | BRAT 2017 | BRAT 2018 | BRAT 2019 |
|---|---|---|---|
| 1 | 0.885 | 0.8866 | 0.8887 |
| 2 | 0.884 | 0.8845 | 0.8889 |
| 3 | 0.882 | 0.8842 | 0.8885 |
| 4 | 0.881 | 0.8834 | 0.8883 |

**Table 2** Comparison of existing works

| | BraTS 2017 | BraTS 2018 | BraTS 2019 |
|---|---|---|---|
| GlaS | 2.04% | 0.788 | 0.706 |
| MoNuSeg, | 1.37 % | 0.909 | 0.871 |
| Kvasir-Seg | 2.74% | 0.825 | 0.771 |
| CVC-ClinicDB, | 1.12% | 0.706(VD) | 0.709(TD) |

In order to maintain the integrity of the fine-grained details and improve the accuracy of the segmentation, U-Net makes use of skip connections between the encoder and the decoder. U-Net places a strong emphasis on spatial interactions and is hence ideally suited for identifying both local and global characteristics present within an image. Due to the fact that U-Net is very simple and quick to put into practice, it has become a popular choice for a variety of segmentation jobs. ATT models are particularly effective at capturing the global context and long-range dependencies in the data, which can be helpful when attempting to gain an understanding of complicated structures such as brain tumors. Attention models employ attention methods to weight the relevance of various parts of the input, which enables the model to concentrate on particular regions of interest.

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## 4Conclusions

For the analysis, the datasets BraTS-2017 BraTS-2018 and BraTS-2019 which consist of High-Grade Glioma (HGG) and Low-Grade Glioma (LGG) MR Scans, have been used for tumour segmentation. We have achieved a dice coefficient of at least 0.8866 and as high as 0.8887 on the discovery cohort, and at least 0.8895 and as high as 0.8911 cross-validation replication cohort Our DCA module shows Dice Score improvements up to 2.05% on GlaS, 2.74% on MoNuSeg, 1.37% on CVC-ClinicDB, 1.12% on Kvasir-Seg and 1.44% on Synapse datasets. Segmenting brain tumours is an important yet challenging process. In this paper, we use the BraTs-2019 software to detect brain tumours in T1-W MRI scans using the U-Net, ATT U-Net, and R2 U-Net models. The effectiveness of every technique was measured using DSC, JI, and the Hausdorff distance. When compared to the U-Net and ATT U-Net, the brain tumour is more accurately segmented by the R2 U-Net model, which also achieves better DSC and JI values. R2U-Net is a flexible option for jobs that require both spatial and temporal context, thanks to its combination of U-Net and recurrent networks' strengths. For better diagnosis of brain tumours in the future, a hybrid model will be used.

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