Development of a Modified UNet-Based Image Segmentation Architecture for Brain Tumor MRI Segmentation

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Abstract. Segmentation of the tumor part on the head MRI image is an important thing that must be done by the radiologist in the patient's diagnosis. Therefore, segmentation must be done accurately because this determines the results of the diagnosis and the determination of the next steps taken by the doctor. Segmentation is currently done manually or automatically with a computer system. Several previous studies have developed a brain MRI image segmentation method for tumors based on deep learning imaging. However, the deep learning architecture developed is composed of complex structures and takes a long time to process. So, this paper discusses the study of the development of a lightweight and accurate image segmentation architecture. We propose a study of changes in the size of the MRI image input from 512 × 512 to 16 × 16 to review its effect on the evaluation using the Dice Coefficient method and visual representation of the image. The smaller the input size, the fewer computational processes will occur so that the processing speed will increase. However, the smaller the input size, the less visible the visual representation of the image is. In addition, a study of modifications to the UNet architecture was also carried out combined with the UBNet classification architecture to compare the performance of the two models. The research was carried out computationally and obtained an average accuracy of more than 95% with a quite different visual appearance.

Keywords: Deep Learning · MRI · Image Segmentation · UNet · UBNet

1 Introduction

Radiography is important in medical diagnosis. Several radiographic methods can be used in medical diagnosis such as X-rays, CT-Scans, and MRIs. In the case of low-glioma, the use of MRI is needed to obtain a better image. The diagnosis and monitoring of low-glioma patients are carried out by segmenting the patient's brain MRI image [1]. The process of segmenting brain MRI images has been done manually, this takes a long time and requires high accuracy. Therefore, it is necessary to develop an automatic brain MRI image segmentation method to reduce time and increase segmentation accuracy.

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Several pattern recognition-based methods have been developed related to brain MRI image segmentation such as SVM [2], fuzzy c-means [2], k-means [2], and Random Forest [3].

The image processing technology is growing rapidly along with the development of computing technology, the application of deep learning methods or image processing based on artificial intelligence is also growing rapidly. One of them is the use of a CNN (convolutional neural network)-based segmentation method called UNet [4]. The use of deep learning-based segmentation methods enables more accurate segmentation results and a shorter time. In previous studies, the SegNet [5], UNet [4], and patch-wise UNet [6] based methods have been applied for brain MRI image segmentation. However, the segmentation carried out aims to obtain the segmentation of White Matter, Gray Matter, and CSF in the MRI image. In this study, a UNet image segmentation method was developed by building a UBNet-based UNet architecture [7]. The UBNet architecture is used as the basis for developing UNet, because UBNet is an architecture that was originally built to process specific X-ray images. So, it is hoped that the use of the UBNet architecture as a UNet development can improve model performance and reduce computing time. This research also analyzes the effect of the input image size on the performance of the UNet and UNet-UBNet models as well as changes in the visual image after processing. Then, a desktop-based GUI was also developed which contains a model that has been trained to facilitate the segmentation process of brain MRI images.

2 Methods

Pre-processing

The dataset used comes from The Cancer Imaging Archive which can be accessed openly for research purposes [8, 9]. The data used consisted of MRI images of 110 patients. The dataset contains MRI images of the brain along with manual FLAIR (fluid-attenuated inversion recovery) abnormality segmentation masks. Figure 1 shows the MRI dataset and the masks used in this study.

Pre-processing is needed to prepare the data so that it can be used to train the model properly. Pre-processing includes image normalization and data augmentation. Data augmentation is done to increase the variation of the dataset when it is used for training.

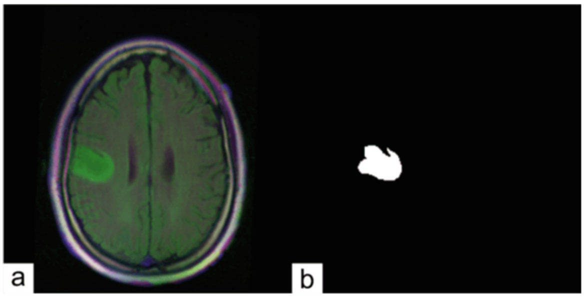


Fig. 1. (a) MRI Image and (b) mask of the MRI Image

The augmentation parameters used include rotation, width shift, height shift, shear, zoom, and horizontal flip. Image size is also adjustable. In this research, image size variations are used 32x32, 64x64, 128x128, 256x256, and 512x512.

Modified UNet Architecture

The development of the segmentation method is carried out by modifying the UNet architecture by building a UNet-UBNet-based UNet architecture. UBNet is an architecture that was built specifically to process X-ray images, so it is hoped that more accurate segmentation results will be obtained and relatively short computation time. The UBNet architecture is shown in Fig. 2.

UBNet v1 architecture consists of 7 convolution layers and 3 artificial neural network layers. In the standard version of UBNet, the input used is 400x400. In this study, different input values will be used to review how they affect the segmentation results. Namely sizes 16x16, 32x32, 64x64, 128x128, 256x256, and 512x512. Then based on the UBNet v1 architecture, an image segmentation architecture was built using the UNet scheme. So that the architecture for the modified UNet image segmentation is obtained based on the UBNet architectural structure. The UNet-UBNet architecture is shown in Fig. 3.

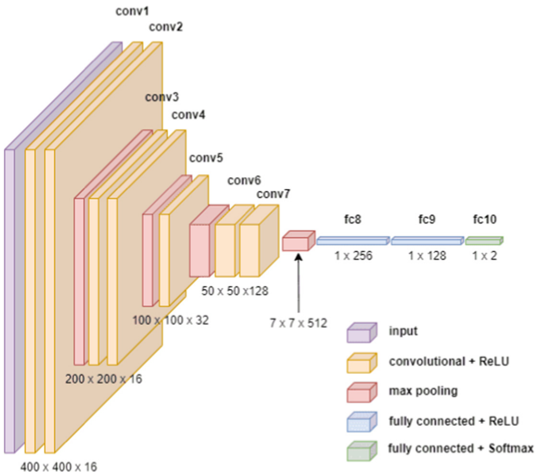


Fig. 2. UBNet v1 Architecture.

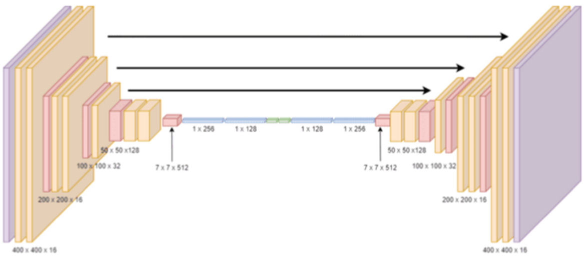


Fig. 3. UNet-UBNet Architecture

3 Result and Discussion

After the training process is carried out by changing the size of the input image, the results obtained are accuracy and loss during the training process. More details are shown in Table 2. The results of accuracy and loss are not much different values. This shows that

Table 1. Comparison segmentation result with different input size.

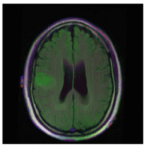
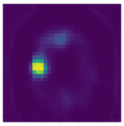
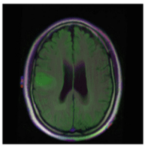
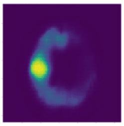
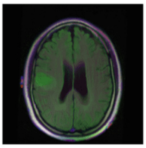
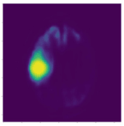
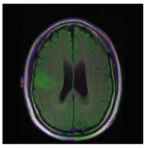
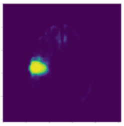
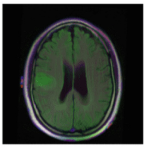
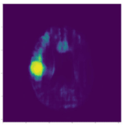
Input Image	Segmentation	Input Size
		32x32
		64x64
		128x128
		256x256
		512x512

Table 2. Accuracy and loss with different input size.

Input Size	epochs	accuracy	loss
32 × 32	30	0.9963	0.0106
64 × 64	30	0.9960	0.0118
128 × 128	30	0.9964	0.0108
256 × 256	30	0.9970	0.0085
512 × 512	30	0.9924	0.0289

the UNet-UBNet segmentation method is quite stable in segmenting with various input image sizes.

Judging from the accuracy and loss values, UNet-UBNet shows a fairly good performance, but if observed visually it will show quite different results. The results of segmentation with the smaller input size will give a fairly rough segmentation output. If viewed from the value of accuracy and loss, then the value will remain high. But visually it looks very different. The results of segmentation with different input sizes are shown in Table 1.

Then a desktop-based GUI was developed that contains the UNet-UBNet model that has been trained so that it can be easily used by radiologists in segmenting MRI images of the patient's brain for the diagnosis of low-glioma. This GUI is built in python. Consists of 2 buttons, namely the image input button and the button to start the segmentation process. In addition, at the bottom left there is a button to select the input image size to be used. The initial view of the GUI is shown in Fig. 4.

In doing segmentation with this GUI is quite easy, just enter the image to be processed and select the input size to be selected. In Fig. 5. And Fig. 6. Shows the GUI that has done the segmentation process.

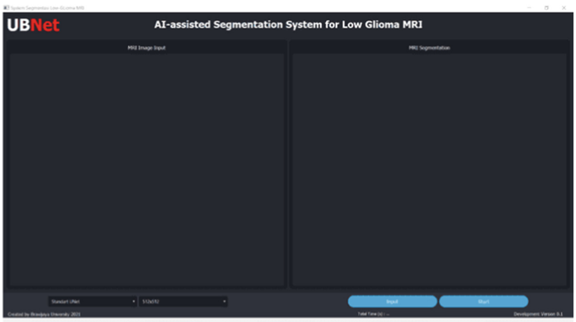


Fig. 4. Initial view of GUI for MRI Brain Segmentation.

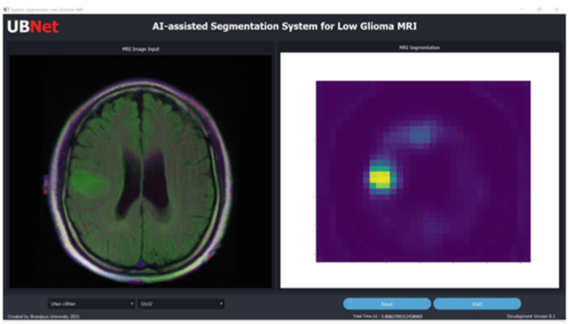


Fig. 5. Segmentation using GUI with input size 32x32.

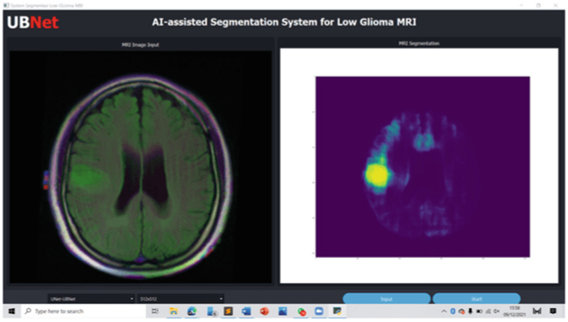


Fig. 6. Segmentation using GUI with input size 512x512.

4 Conclusions

The UNet-UBNet image segmentation architecture can be used to process brain MRI images and perform segmentation well. Changes in input size have no significant effect on accuracy and loss in the UNet-UBNet model. However, it is still quite influential on the visual appearance of the segmentation results. The smaller the input image size, the coarser the segmentation results. Meanwhile, the larger the size of the input image used, the more detailed the segmentation results will be. The GUI that was built can work well and make it easier to segment the brain MRI images of low-glioma patients.

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