

## U-Net Analysis Architecture For MRI Brain Tumor Segmentation

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### Article Information

#### Article history:

No. 713

Rec. April 17, 2023

Rev. November 23, 2023

Acc. November 23, 2023

Pub. November 30, 2023

Page. 126 – 138

#### Keywords:

- brain tumor segmentation
- MRI
- U-Net
- number of neurons

### ABSTRACT

Identification, segmentation and detection of brain tumor-infected parts on MRI images require precision and a long time. MRI of the brain has an important role, one of which is used for analysis or consideration before performing surgery. However, MRI images cannot provide optimal results when analyzed because of the presence of noise and the bone and tumor (clots of flesh) have the same appearance. Many studies related to brain tumor segmentation have been carried out before, and some of the good methods are CNN U-Net. We segmented brain tumors on MRI with U-Net. The purpose of this study was to analyze the results of changes in the number of neurons in the convolution layer of the U-Net architecture in segmenting brain tumors. We use two scenarios of changing the number of neurons at the U-Net convolution layer. The first scenario is the number of neurons successively at each level of the U-Net architecture [32,64,128,256,512], and the second scenario is [16,32,64,128,256]. And the results of scenario two can segment brain tumors on MRI images that resemble ground truth. The results of brain tumor segmentation in MRI images with the U-Net second scenarios have an average Dice value of 0.768.

#### How to Cite:

Nafi'iyah. N., et al. (2023). U-Net Analysis Architecture For MRI Brain Tumor Segmentation. Jurnal Teknologi Informasi Dan Pendidikan, 16(2), 126-138. <https://doi.org/10.24036/jtip.v16i2.713>

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## 1. INTRODUCTION

A brain tumor is a condition that causes fleshy growth inside the brain [1]. The human brain serves as the body's nerve center, a crucial function. Can use magnetic resonance

imaging (MRI) or magnetic resonance imaging technology to find human malignancies. An organ, tissue, or skeletal system can be examined and recorded using magnetic resonance imaging technology known as MRI [2],[3]. The brain is essential because it is the center of the nervous system that controls all human activities. Therefore, brain MRI plays an important role, one of which is used for analysis and review before surgery. However, MRI images may not provide the best analysis results because the noise and bone and tumor (lumps of flesh) look the same. With the development of AI (artificial intelligence), digital image processing, and computer vision, MRI images can be analyzed and segmented to detect or identify tumors correctly.

Brain MRI images cannot accurately diagnose a patient's disease because the noise, tumor tissue, and other tissues are the same color. However, several previous studies have shown that tumors in the brain can be found by segmenting brain MRI images [4],[5],[6]. However, brain tumor segmentation presents a challenge as brain tumors exhibit different intensities on MRI images. Therefore, various studies have developed brain tumor segmentation methods to accurately and precisely determine the shape and size of brain tumors. It includes a segmentation method: thresholding [1], segmentation Superpixel [4],[6], network based ResU-Net [5],[7], network deep learning U-Net [8],[9],[10], D-SEG clustering [11], deep learning Convolutional Neural Network [12], Gaussian Mixture Model [13], SVM (Support Vector Machine) [14], M-Net Convolution [15].

One of the stages of identifying a brain tumor based on artificial intelligence is segmenting the tumor part on a brain MRI image. Accurate and precise segmentation of brain tumors can provide appropriate treatment measures. Based on the importance of adequately segmenting the brain tumor section, we will segment the brain tumor on the MRI image. Based on previous research, the CNN U-Net method has an error rate of 3% in segmenting [8], 2% [9]. We segmented brain tumors on MRI with the U-Net method. This study aimed to modify and analyze the number of U-Net convolution layer neurons in segmenting brain tumors on MRI images.

## 2. RESEARCH METHOD

To segment brain tumors on MRI images, this study examines the number of neurons in the convolution layer using the U-Net architecture.

The dataset we use is taken from the Kaggle dataset [16]. The distribution of the training and testing datasets is shown in Table 1. Table 1 the total training data is 115 MRI images that all contain tumors, and the ground truth is black and white (black is the background, and white is the tumor). We use an input image that already contains ground truth from the Kaggle dataset [16]. The CNN (Convolutional Neural Network) method is a significant deep learning method that can recognize images [17]. In addition, the CNN (Convolutional Neural Network) method can be used for image reconstruction in either 2D or 3D [18], In addition to using deep learning, the process of identifying images can also use machine

learning [19]. The CNN (Convolutional Neural Network) model input image is segmented based on ground truth image learning. The original MRI images and their respective ground truths are in Table 2. The data used to create the model are all training MRI images that contain tumors, and black and white ground truth images (black background, and white is the tumor), as in Table 2.

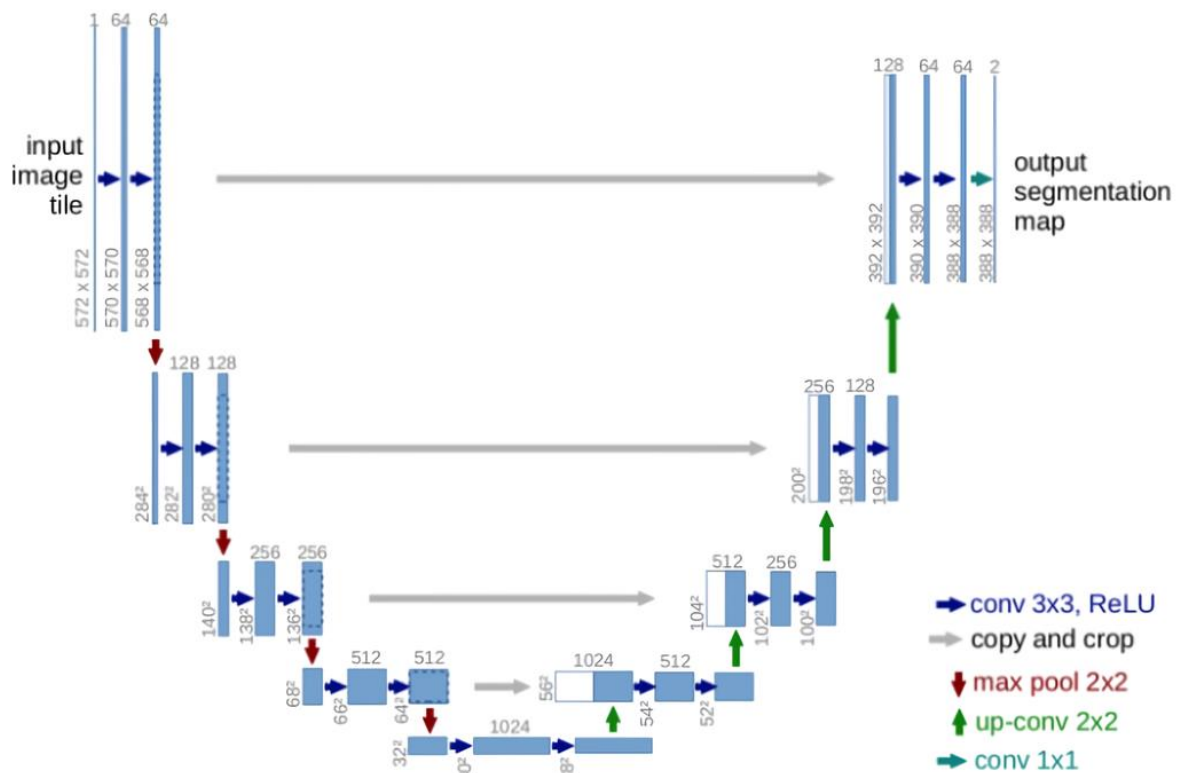
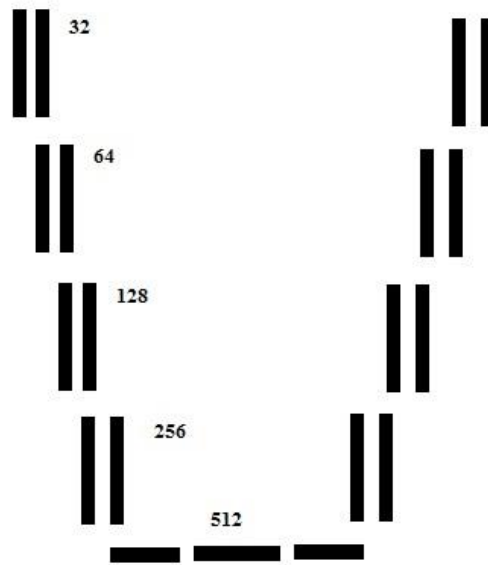
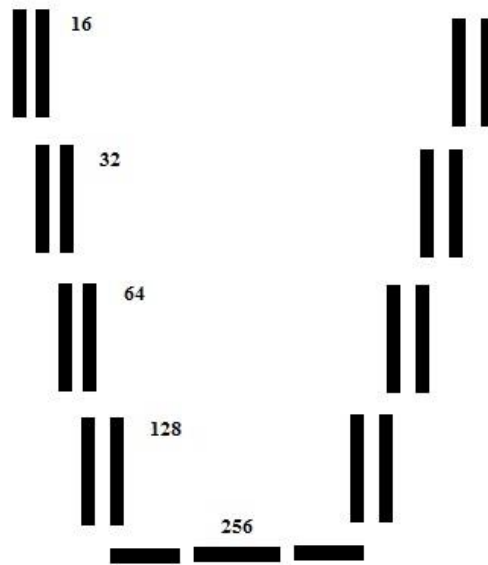


Figure 1. U-Net Architecture



(a)



(b)

**Figure 2.** Modification of U-Net convolution layer neurons (a) Scenario 1 (b) Scenario 2

**Table 1.** Dataset

Image	Total
Training	115
Testing	28
Total	143

Table 2. Image data

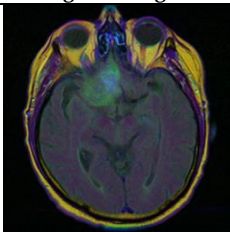
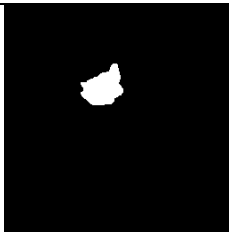
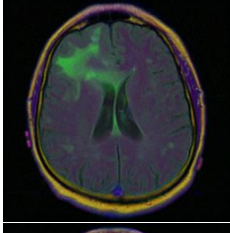

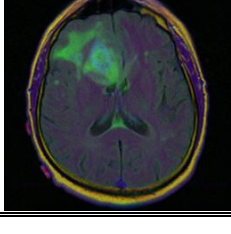
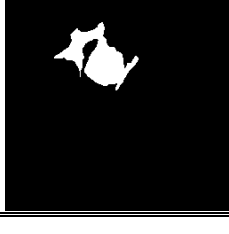
Original image	Ground truth
	
	
	


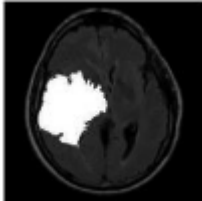

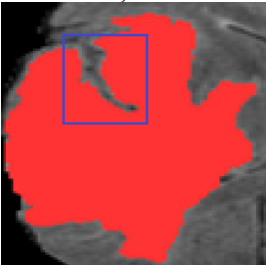
Table 3. Parameters

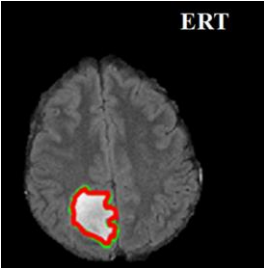

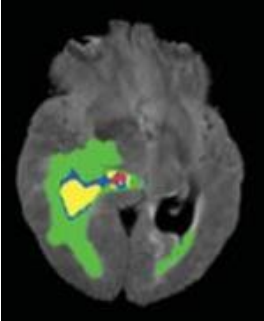

Architecture	Layer convolution	Total parameter
U-Net	[64,128,256,512,1024]	31,378,945
U-Net Scenario 1	[32,64,128,256,512]	7,846,657
U-Net Scenario 2	[16,32,64,128,256]	1,962,625

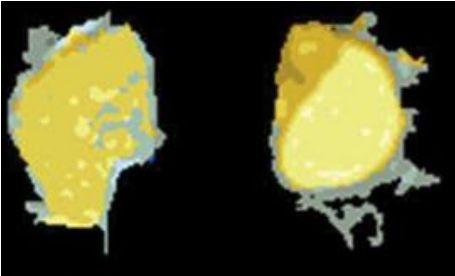
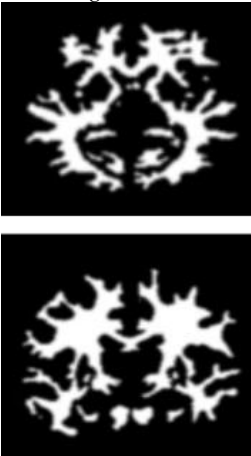
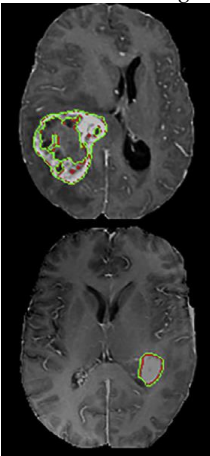
The original U-Net architecture, as in Figure 1 [8]. The encoder (left side) and decoder (right side) stages comprise the U-Net architecture. A convolution and pooling layer is present in each component of the encoder and decoder. Four levels or depths made up the original U-Net in Figure 1, and we kept the same number of depths in the architecture. The segmented image is 256x256, and the final image will be the same size. As seen in Figure 2, we suggest adjusting the number of neurons in each convolution layer of the encoder or decoder. The number of parameters in the U-Net design will change as the number of neurons in the convolution layer changes.

In each convolution layer, we offer two scenarios for the number of neurons: the number of neurons defined as [32,64,128,256,512] and the number of neurons described as [16,32,64,128,256]. The original number of neurons from each convolution layer of the U-Net architecture is [64,128,256,512,1024] (Figure 1). Table 3 describes the number of parameters for each scenario and the original U-Net architecture. Table 4 describes several researches related to brain tumor segmentation.

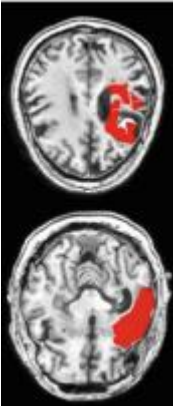
**Table 4.** Brain tumor segmentation research

No	Method	Results
1	Binary thresholding	Segmenting brain tumors by thresholding and contouring [1] 
2	Active contour	Active contour method of segmenting brain tumors on MRI images and analyzing the results [3] 
3	Clustering with superpixels	A clustering method based on superpixels to segment brain tumors [4] 
4	ResU-Net	ResU-Net objects brain tumor detection and segmentation [5] 
5	Superpixel and ERT (Extremely Randomized Trees)	ERT method of segmenting brain tumors [6]

No	Method	Results
6	U-Net	 <p>ERT</p> <p>Deep learning U-Net brain tumor segmentation [8]</p>
7	U-Net	 <p>Deep learning U-Net and ResU-Net brain tumor segmentation [9]</p>
8	U-Net	 <p>Segmentation of Brain Tumors Based on Magnetic Resonance Imaging Images using the U-NET Method [10]</p>
9	D-Seg	 <p>Brain tumor classification using the diffusion tensor image segmentation (D-SEG) technique [11]</p>

No	Method	Results
10	CNN	 <p data-bbox="662 615 1247 667">Using a Patch-Wise M-Net Convolutional Neural Network for Tissue Segmentation in Brain MRI Images [15]</p>
11	U-Net	 <p data-bbox="662 1125 1089 1146">Modified U-Net segmented brain tumors [20]</p>
12	Depthwise separable convolution based X-Net	 <p data-bbox="662 1608 1230 1661">X-Net: Brain stroke lesion segmentation based on depthwise separable convolution and long-range dependencies [21]</p>



No	Method	Results
		


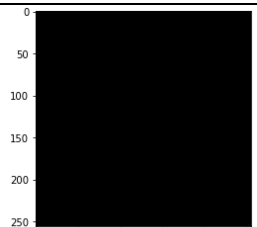
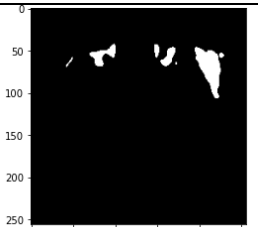
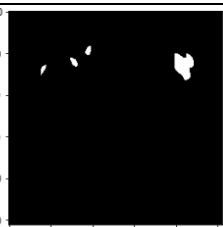
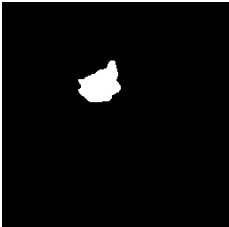
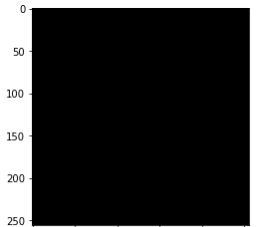
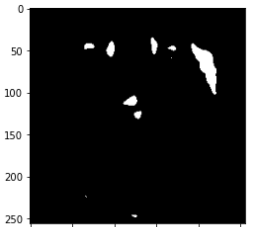

### 3. RESULTS AND DISCUSSION

On MRI scans, we segmented brain tumors based on the number of neurons in the U-Net architecture. Table 5 displays the segmentation findings for brain tumors from the original U-Net and design scenarios 1 and 2. How We calculated Dice, as in Equation 1, to evaluate [7]. Based on Table 5, the results of the original U-Net method could have been better in segmenting brain tumors. While the results of scenario one show cancer but it is too over.

$$Dice(A, B) = \frac{2|A \cap B|}{|A| + |B|} \tag{1}$$

Equation 1: A is the image resulting from segmentation, and B is the ground truth image.

**Table 5.** Brain tumor segmentation results

Ground truth	U-Net	U-Net Scenario 1	U-Net Scenario 2
			
			

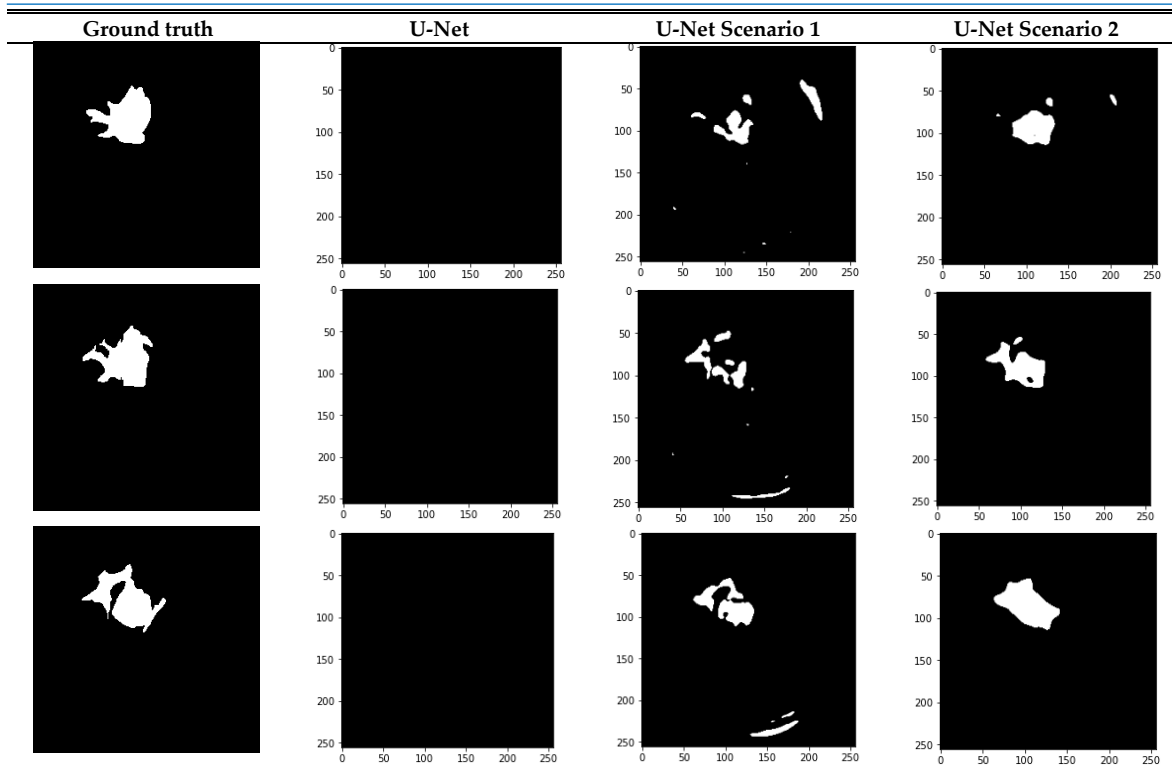


Table 6. Dice result

U-Net Original	U-Net Scenario 1	U-Net Scenario 2
0	0.76	0.768

We train the data on the original U-Net architecture and scenarios 1 and 2 with optimizer="adam", and function loss="binary crossentropy", 50 epochs and each epoch reads 110 image data. Based on the evaluation results of brain tumor segmentation, it is shown in Table 5. From the visual results of scenario 1, it can be seen that all parts of the brain tumor have been segmented. However, there is an over section, and the average Dice result in scenario 1 is 0.76. From observations of the results of scenario 2 segmentation visually close to ground truth, however in Table 4 the first and second images do not resemble ground truth, so the average Dice result for scenario 2 is 0.768. We present visual results of brain tumor segmentation from several previous studies in Figure 3.

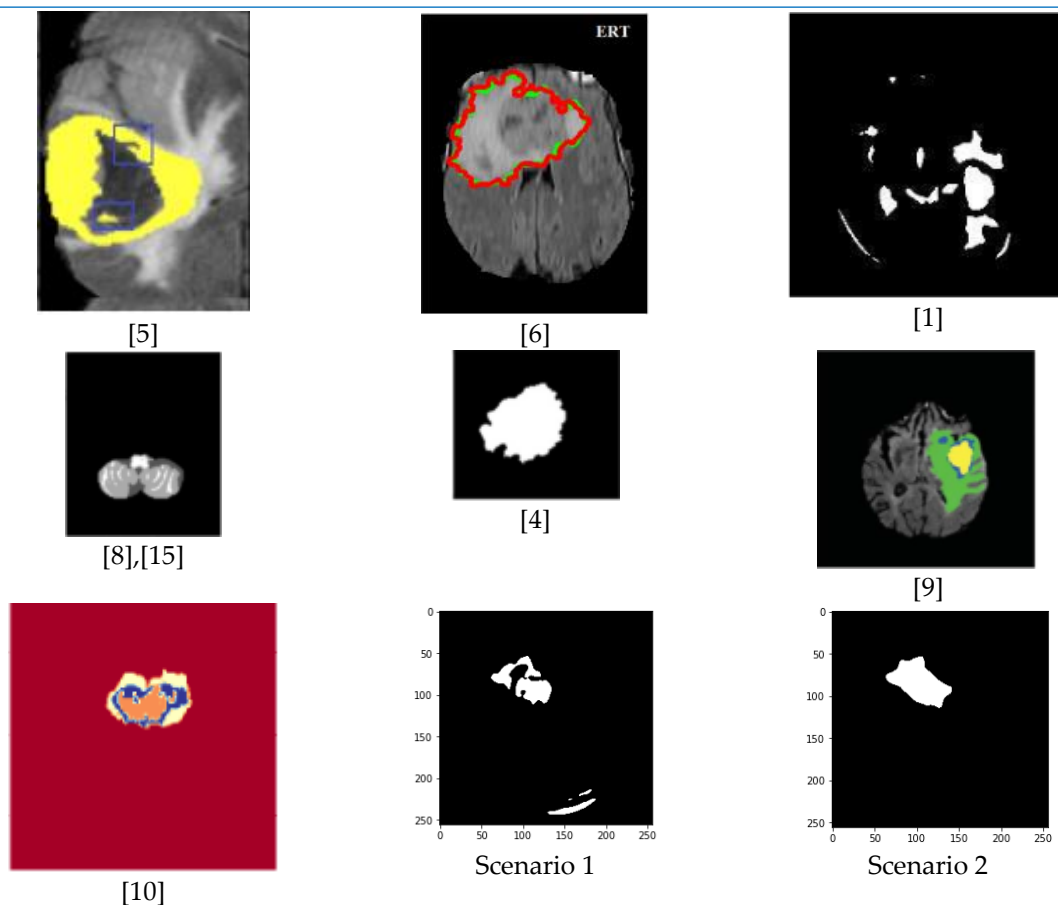


Figure 3. Brain tumor segmentation results

#### 4. CONCLUSION

We segmented brain tumors by U-Net architecture. We alter the U-Net architecture's convolution layer's neuron count. The results of the original U-Net method for segmenting brain tumors on MRI images very poor. The results of brain tumor segmentation with scenario one U-Net can show details of the brain tumor, there is overlap. And the results of scenario two U-Net are better in segmenting brain tumors both from the visual appearance and the average value of Dice.

The next research suggestion is to segment brain tumors in MRI images using other CNN methods so that the segmentation results are more precise.

#### ACKNOWLEDGEMENTS

Thanks to Univeristas Islam Lamongan.

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