International Journal of Membrane Science and Technology, 2023, Vol. 10, No. 1, pp. 249-253

Breast Cancer Image Semantic Segmentation with Attention U-Net

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Abstracts: Semantic segmentation is to segment objects in an image into meaningful units. Among them, the basic idea of U-Net is to use low-dimensional as well as high-dimensional information to extract image features and enable accurate location identification. In this paper, we present a new model that combines Attention Gates with U-Net and evaluate the results through semantic segmentation with breast cancer datasets. To this end, this study proposes and tests a methodology for breast cancer image segmentation based on Attention U-Net. In conclusion, when comparing the performance with the existing U-Net, It can be seen that IoU is 0.069 higher than the existing U-Net. Thus, the proposed model enables better image semantic segmentation.

Keywords: Semantic Segmentation, U-net, Soft Attention, Attention gate, Sigmoid, Decoder

1. INTRODUCTION

In recent years, artificial intelligence research has been applied to various industrial fields with rapid development. In particular, in the medical field, studies targeting organs or diseases are being conducted in CT and X-ray images and photos[1]. In particular, the use of semantic segmentation techniques increases the accuracy of the detection of diseases such as cancer, giving medical staff and researchers higher convenience and effectiveness in early diagnosis and treatment. Deep learning-based segmentation models have been proposed in various forms since the advent of fully convolutional networks (FCNs), especially structures such as Unet, deeplab v3+, and Pspnet are widely used for image segmentation.

Breast cancer is one of the most common causes of death among women worldwide. Early detection helps in reducing the number of early deaths. Unlike real pictures, medical pictures look very much like each other. They are obtained using similar parameters at standardized locations. For radiologists, the experience of interpreting images stems from knowing exactly where to look to find a particular disease. So it's not surprising that Attention played a big role in medical image analysis before other areas of research. In the meantime, the network (U-Net, FCN..) has been proposed to view the entire CT image to detect and classify the disease. This resulted in multi-label classification using BCE as a loss function or an encoder-decoder structure using LSTM as a decoder to capture interdependencies between labels [2]. The problem with using the entire CT image for classification is that the lesion area in the medical image may be very small compared to the entire image and may even be located along the boundary, causing a lot of noise in the classifier and reducing detection accuracy. Moreover, CT line images are often misaligned. (Second row in Figure 1 below) This alignment error will negatively affect classification performance by making the boundaries around the image irregular. In this paper, using soft attention for breast cancer image segmentation, when the soft attention technique is combined with U-Net (which is called Attention U-Net), we can derive much better segmentation results even with very few additional parameters compared to ordinary U-Net for three-dimensional abdominal CT image segmentation.

2. RELATED WORK

2.1 U-Net

U-Net is a fully-convolutional network-based model of the end-to-end scheme proposed for image segmentation in the biomedical field. It was named U-Net because of its network configuration ('U') [2, 3, 10, 11]. A network for obtaining the overall context information of the image and a network for accurate localization are constructed in a symmetrical form. For Expanding Path, several Up-sampling are performed to obtain higher resolution segmentation results from the final feature map of the Contacting Path. In other words, it is a structure for obtaining Dense Prediction in the Coarse Map. Since U-Net is an expanded concept based on a fully convolutional network (FCN), it is desirable to understand FCN first to help clear understanding. In addition to the Coarse Map to Dense Map concept, U-Net has also proposed a scheme to combine shallow layer feature maps with deep layer feature maps, utilizing the Skip Architecture concept of FCN. The combination of the feature hierarchy of these CNN networks allows us to solve the trade-off between Segmentation-enclosed Localization and Context (Semantic Information)[4].

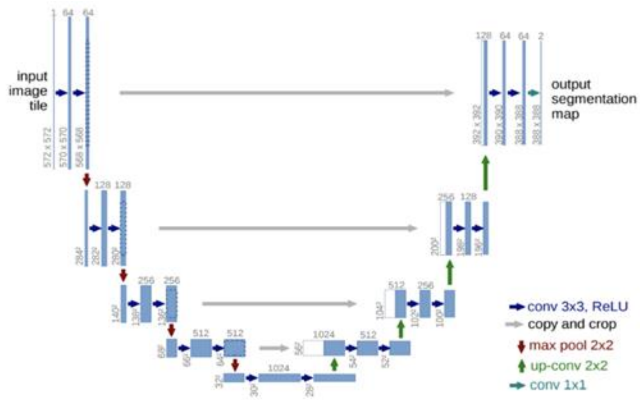

Figure 1. Structure of U-Net.

2.2 Attention gate

The Attention Network showed a lower error rate on the CIFAR dataset as well as a lower computational volume than the existing SOTA model, and a lower value error rate on the ImageNet dataset. In this paper, there are three contributions: 1) Stacked Network Structure extracts only one feature per module, but learns to detect different types of attention using multiple attention modules. 2) Simply stacking the attention module with Attention Residual Learning reduces its performance, which is improved with Residual Learning. 3) It is characterized by additional weight.

The module proposed in this paper is shown in the figure above, and there are Soft Mask Branch and Trunk Branch as 2-branch [5, 6, 8, 9].

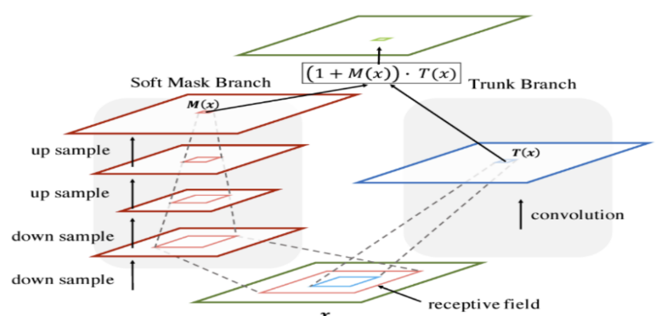

Figure 2. Attention architecture - Soft Mask Branch and Trunk Branch as 2-branch.

3. NETWORK RELATED

In this paper, Attention-U-Net was used. This is because this module introduced an attention gate (AG) that uses soft Attention. Using soft attention, only activation of the required area can be emphasized through Skip-Connection, which improves the problem of overlapping features in Skip-Connection of existing U-Net. In addition, the lack of feature expression in the Up sampling process is improved through Gating Signal. In the process of sending low-dimensional feature values from U-Net to high-dimensional, the Attention Gate was used to weight the important parts more importantly and the unnecessary parts lower to make more accurate predictions by using Attention U-Net, which reflects only the important parts of low-dimensional features when predicting breast cancer location.

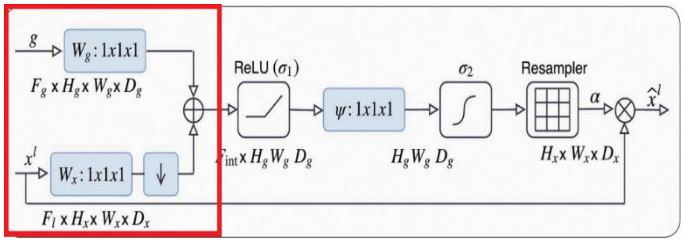

Figure 3-1. Attention gate Architecture(1).

Looking at Figure 3-1, we calculate the attention coefficient α through x and g, and then multiply it by x and elementwise again to create a feature map x^ that reflects the weight of each feature.

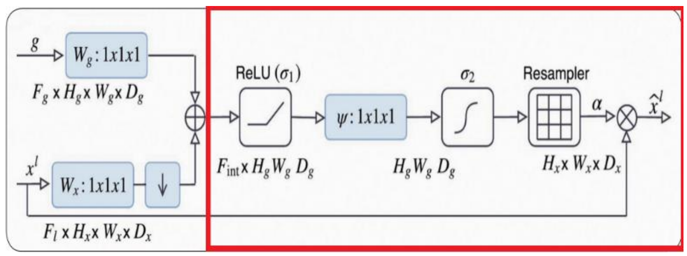

Figure 3-2. Attention gate Architecture(2).

In other words, the attention gate's role is to multiply the encoder's feature map x by a grid-specific weight (α) that activates the core area more before skipping connection to the decoder, and to get more information needed to calculate α, it can identify the processing of sigmoid and linear units. As learning progresses, the activity of areas with low relevance to the purpose decreases, and the activity of important areas such as the location of the cancer increases.

4. EXPERIMENT

4.1. Datasets

Breast cancer is one of the most common causes of death among women worldwide. Early detection helps in reducing the number of early deaths. The data reviews the medical images of breast cancer using ultrasound scan. Breast Ultrasound Dataset is categorized into three classes : normal, benign, and malignant images. Breast ultrasound images can produce great results in classification, detection, and segmentation of breast cancer when combined with machine learning. The data collected at baseline include breast ultrasound images among women in ages between 25 and 75 years old.

4.2. Data Approach

This data was collected in 2018. The number of patients is 600 female patients. The dataset consists of 780 images with an average image size of 500*500 pixels. The images are in PNG format. The ground truth images are presented with original images. The images are categorized into three classes, which are normal, benign, and malignant. All the images are of 500 X 500 pixels, Kaggle RAM will not be enough so we will be resizing the Image to 256 X 256 pixels.

4.3. Results

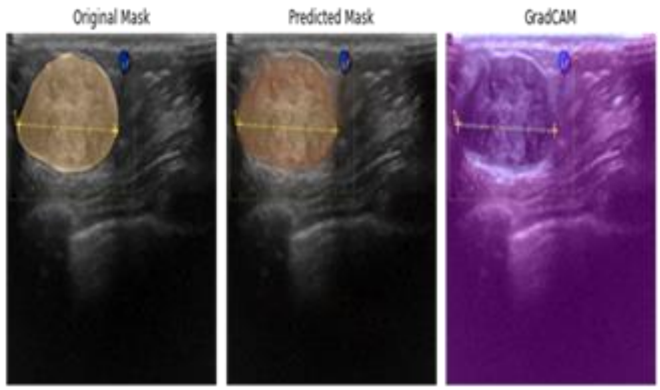

Figure 4. Image segmentation comparison between original mask of breast cancer CT image and predicated mask and Grad-CAM applied attention unit proposed in the paper.

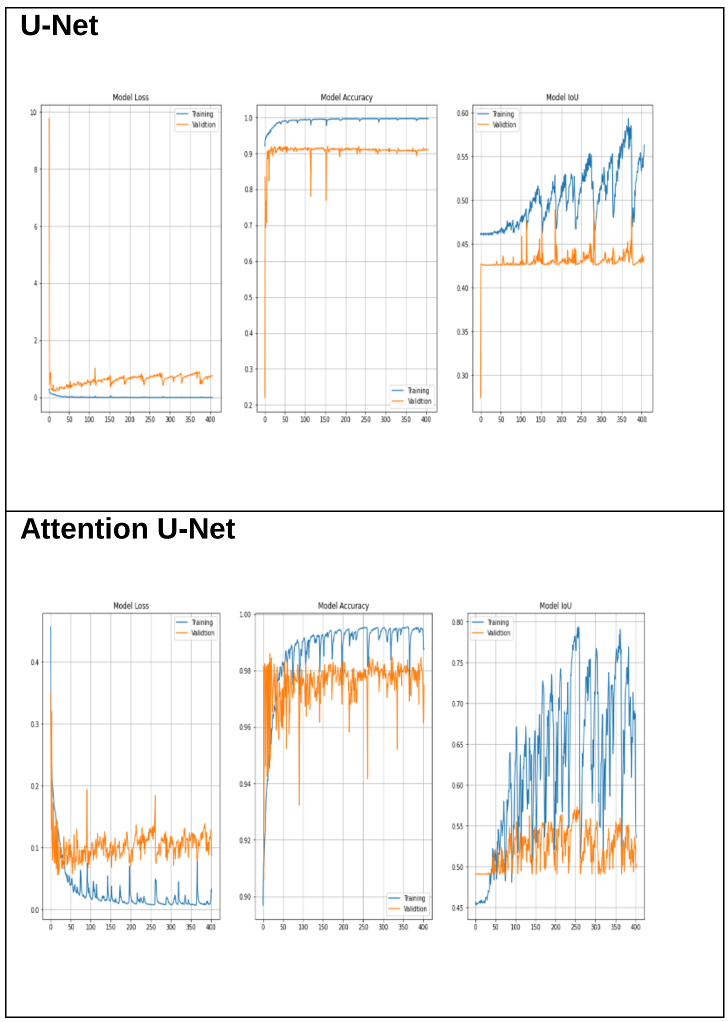

Figure 5. Performance Comparison of U-Net and Attention U-Net(1).

	Accuracy	loss	IoU	Val_Accuracy	Val_loss	Val_IoU
U-Net	0.987	0.029	0.535	0.911	0.770	0.434
Att-UNet	0.997	0.003	0.562	0.974	0.087	0.503

Figure 6. Performance Comparison of U-Net and Attention U-Net(2).

Do training in chunks of 500 Epochs, this will give you a good control over model and the model will also perform well.

If you give the model a closer look n different images you will find that the model fails at some images, but I can guarantee that 9/10 such images would be so tough that even a human will not be a able to detect as many parts of the image look the same. Surprisingly the results on Validation Data are way better than the results on Trained Data on IoU, this may indicate that the model can perform way better than what it can do at the current point. The Loss is not Perfect it increases in the last but the model constructions are looking perfect as this point.

5. CONCLUSION

The application of Attention U-Net-based images shows that the proposed model has better performance than the existing model through loss, accuracy, and IOU results in train and validation than the existing U-Net. Through this study, it is expected that it will be applied to future medical technologies and have excellent effects in the medical community. As a point of consideration, it was not possible to properly compare the number of learnings and the performance due to the time limit. Therefore, in the next study, the normality test of the data will be conducted through a much larger number of learning times and a shapiro-wilk test.

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DOI: https://doi.org/10.15379/ijmst.v10i1.1452