American Scientific Research Journal for Engineering, Technology, and Sciences (ASRJETS)

ISSN (Print) 2313-4410, ISSN (Online) 2313-4402



http://asrjetsjournal.org/

# MRI Image Segmentation System of Uterine Fibroids Based on AR-Unet Network

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**Abstract**

Uterine fibroids are the most common benign tumors in female reproductive organs. The segmentation of uterine fibroids is crucial for accurate treatment. This paper proposes a new uterine fibroids MRI T2W image segmentation network AR-Unet (Attention Resnet101-Unet), which uses the deep neural network ResNet101 as the front end of feature extraction, extracts image semantic information, and combines U-net design ideas to build a network structure. The attention gate module is added before the upsampling and downsampling feature maps are spliced. We tested a total of 123 uterine fibroids MRI T2W images from 13 patients. The segmentation results were verified with expert-defined manual segmentation results. The average Dice coefficient, IOU value, sensitivity and specificity of all segmented images were 0.9044, 0.8443, 88.55% and 94.56%, the performance is better than ResNet101-Unet and Attention-Unet models, and finally the network is encapsulated into an auxiliary diagnostic system.

***Keywords:*** Uterine fibroids MRI image segmentation; Attention ResNet101-Unet; Attention mechanism.

## 1. Introduction

Uterine fibroids are the most common benign tumors of the female reproductive system, which are common in women aged 30-50 years [1].

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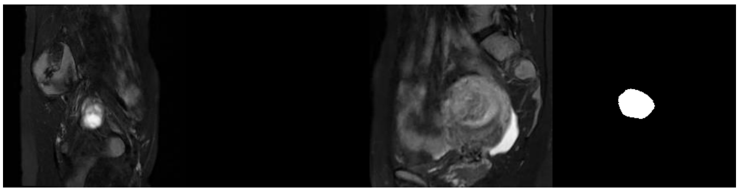
According to statistics, at least 25% of women of childbearing age in China have uterine fibroids [2]. In fact, because many patients have no obvious symptoms, the actual incidence of uterine fibroids is much higher than the above data. It can cause uterine bleeding, pelvic pain, abdominal masses and compression symptoms, infertility, premature delivery and miscarriage, which seriously affects the normal life of Chinese women and places an economic burden on families and society. Therefore, early uterine fibroids screening can enable patients to detect early, thereby increasing the chance of recovery. Screening methods incl- ude ultrasound, hysteroscopy and MRI, of which MRI is currently considered to be the most accurate imaging technique for detecting and locating fibroids [3]. However, segmentation of MRI images of uterine fibroids is a challenging task, which is usually done manually by one or two experienced doctors. Because the borders of fibroids are usually blurred in the image and there are noisy textures and artifacts inside, manual segmentation of uterine fibroids will cost the doctor a lot of energy and time. Because different doctors have different levels of diagnosis, and there will be missed and misdiagnosed cases, it is of great significance to study the automatic and accurate segmentation of uterine fibroids. In order to help doctors improve the accuracy and efficiency of MRI image segmentation of uterine fibroids, researchers have done a lot of preparation work. In terms of classic algorithms, Yao J. and his colleagues [4] use a method based on the combination of fast-travel level sets and Laplace level sets on MRI images. The seed point is placed in the fibroid area, firstly, the fast-travel level set is used for coarse segmentation, and then the Laplace level set is used for fine segmentation. The average Dice coefficient of all uterine fibroids was 0.711, the average IOU value was 0.812, the average sensitivity was 84.6%, and the average specificity was 84.3%. Khotanlou H. and his colleagues [5] used a two-step method based on Chan-Vese level set method and geometric prior model on MRI images. By using the Chan-Vese level set method to calculate the initial region inside the object, a rough segmentation can be obtained, and then a priori shape model is used for fine segmentation. The average Dice coefficient of all uterine fibroids was 0.8770, the average IOU value was 0.7862, the average sensitivity was 84.49%, and the average specificity was 93.14%. Fallahi A. and his colleagues [6] first used fuzzy c-means (FCM) algorithm to segment the uterus from the enhanced MR data set. Some thinning operations have been applied to the uterine part to remove redundant parts. Then, apply the improved likelihood fuzzy c-mean (MPFCM) algorithm on the registered T2w MR images and perform some post-processing operations in sequence to segment the fibroids. The average Dice coefficient of all uterine fibroids was 0.7954, the average IOU value was 0.6839, the average sensitivity was 75.32%, and the average specificity was 89.51%. Rundo L. and his colleagues [7] proposed a new method for segmentation of fibroids in MR images based on an improved direct region detection model. Through the adaptive region growing process, the results of the split and merge algorithm are used as the selection of multiple seed regions. Then, refine the segmented tumor. The average Dice coefficient of all uterine fibroids was 0.8757, the average IOU value was 0.7850, the average sensitivity was 84.05%, and the average specificity was 92.84%. The traditional algorithms adopted by the above researchers [4,5,6,7] are mostly semi-automatic segmentation, which not only requires human participation, but also has poor robustness and weak applicability. In terms of deep neural networks, Kurata Y. and his colleagues [8] proposed the use of improved U-net for segmentation of uterine fibroids MRI images, that is, replacing the ReLU of each layer in the original U-net network with leaky-ReLu, And increase the dropout layer, using a batch size of 15, down sampling using 8 layers, and finally measured the average Dice coefficient of all uterine fibroids is 0.85. However, document [8] is only a small-scale modification of the original U-net, the network learning ability is lacking, and the image segmentation results need to be improved. In order to improve the segmentation quality, we propose an AR-Unet (Attention Resnet101-Unet) network to segment uterine fibroids MRI images. The main content and structure of this article are as follows: In Section 2, we introduce the data set and pre-processing process, and Section 3 details the network design, parameter analysis, and evaluation indicators. In Section 4, we give the comparison results of segmentation experiments with AR-Unet, ResNet101-Unet and Attention U-net networks, and carry out the proposed method through four evaluation indicators of Dice coefficient, IOU, Sensitivity and Specificity. Analysis and evaluation. In Section 5 we introduce the auxiliary analysis interface of our system. A brief discussion is given in Section 6.

## 2. Data sets and preprocessing

The uterine fibroids data set used was provided by the hospital we worked with. The data set contains a total of 2410 MRI T2W images of 93 patients, which are divided into two categories: no uterine fibroids and uterine fibroids MRI T2W images. In order to enable the network to better learn uterine fibroids image information, we deleted most of the images without uterine fibroids, leaving 970 images with uterine fibroids, and randomly selected 80 patients with a total of 847 images As the training set, a total of 123 images of 13 patients were selected as the test set. The original image size is 240×240, and it is adjusted to 320×320 after being input to the network. The labels of all images are manually marked by professional doctors in the hospital. Figure 1 shows the uterine MRI T2W images and labels.



(a) (b) (c) (d)

**Figure 1:** (a) MRI T2W image without uterine fibroids, (b) No uterine fibroids MRI T2W image label, (c) Contains MRI T2W images of uterine fibroids, (d) Contains MRI image label of uterine fibroids

## 3. Network construction and parameter analysis

### *3.1. Network Framework*

Figure 2 shows the AR-Unet network structure and overall process. First, we adopt the ResNet101 [9] network as the feature extraction module. In order to meet the needs of feature extraction, the structural body of ResNet101 is retained, and the last three layers used for the output of classification results are discarded. The 320×320×1 uterine fibroids MRI image is input to the ResNet101 feature extraction module at the front end of the network, and finally a 10×10×2048 feature vector is obtained, and the downsampling process is completed. We use the transposed convolution method to achieve the upsampling process. The specific operations are as follows: set the transposed convolution layer with a step size of 2 and a convolution kernel size of 2×2, which can gradually increase the size of the feature layer. At the same time, the depth of the feature layer is reduced;

with the U-Net network as the main body, the feature map of the upper layer upsampling and the same layer of the downsampling feature map are adjusted to the same size, and the optimized same layer is obtained by the attention gate module [10]. Downsampling feature map, using feature layer concatenation (concatenate) method, combined with the same scale information in the downsampling line and the upsampling line; after each stitching, use 3×3 convolution layer, batch normalization layer (batch normalization) layer), the ReLU activation function combines the feature information of the same scale, repeats the upsampling operation to obtain a 160×160×64 feature layer, and finally uses a 1×1 convolution layer and a bilinear interpolation method to obtain 320×320×1 Segmentation result.

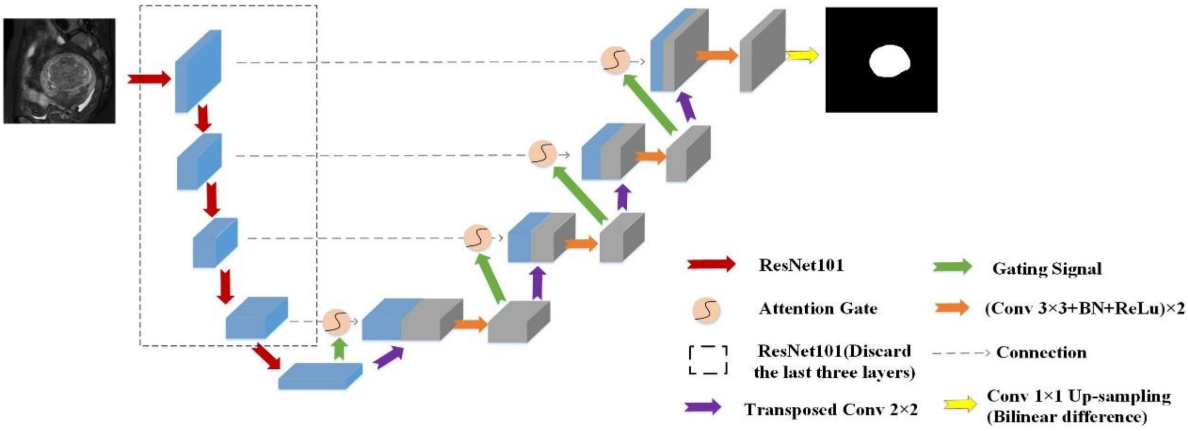
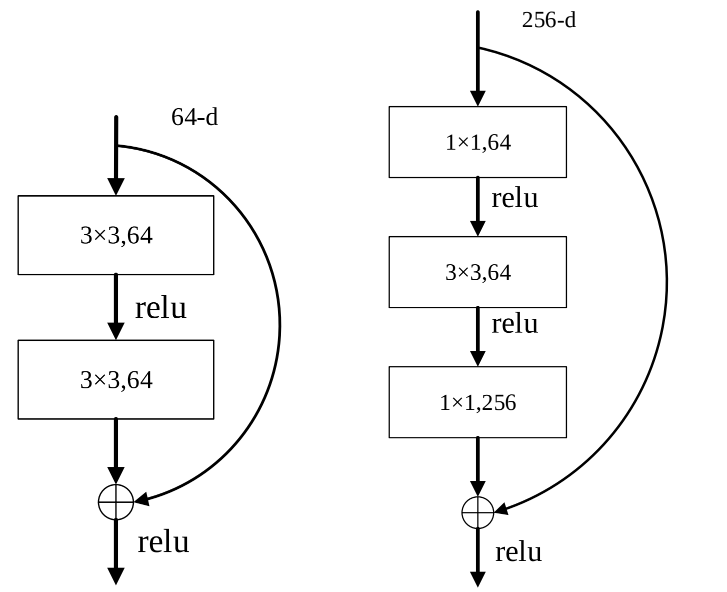



**Figure 2:** the framework of AR-Unet

The network uses ResNet101 as a feature extraction module, which deepens the number of Unet layers and improves the segmentation accuracy. Combined with the attention gate module, without reducing the amount of calculation, it suppresses the activation of irrelevant regional features and improves the sensitivity and accuracy of the model.

### *3.2. ResNet101 module*

ResNet101 network is an improvement of ResNet network. It contains 33 improved residual modules. The ResNet residual module and ResNet101 residual module are shown in Figure 3(a)(b) respectively. The ResNet101 residual module has optimized the ResNet residual block, that is, two 3×3 Is replaced by 1×1 + 3×3 + 1×1. The 3×3 convolutional layer in the middle of the new structure first reduces the calculation under a dimension reduction 1x1 convolutional layer, and then restores it under another 1×1 convolutional layer, which not only maintains accuracy but also reduces the amount of calculation.




(a) ResNet residual module (b) ResNet101 residual module

**Figure 3:** Residual module part

In order to meet the needs of feature extraction, the proposed network retains the main body of the ResNet101 network, discards the last three layers used for the output of the classification results, and the benefits of using the ResNet101 network as a feature extraction module have the following points: 1. Deepen the number of network layers, improve the segmentation accuracy of the network; 2. More jump connections can be added in the middle of the network, so that the background semantic information of the image can be better combined to perform multi-scale segmentation; 3. ResNet101 has fast Convergence, the advantage of reducing the amount of model data; 4. ResNet101 makes the model easier to train, not only can prevent the model from degenerating, but also prevents the gradient from disappearing, and Loss does not converge.

### *3.3. Attention gate module*

The structure of the attention gate module is shown in Figure 4, g represents the upper layer feature map of upsampling, $x^l$ represents the feature map of the same layer downsampling, the two feature maps are adjusted to the same size, and then added, obtained by ReLu and Sigmoid Attention coefficient a (value 0-1), after multiplying with $x^l$, get $x_2^l$feature map, focus attention on the target area, thus emphasizing the characteristics of the salient area of this layer. The increased attention gate module has the following advantages: 1. It can better realize the attention to the saliency area and the suppression of the irrelevant background area; 2. The attention module can be well embedded in the Unet network without increasing the calculation At the same time improve the performance of the model.

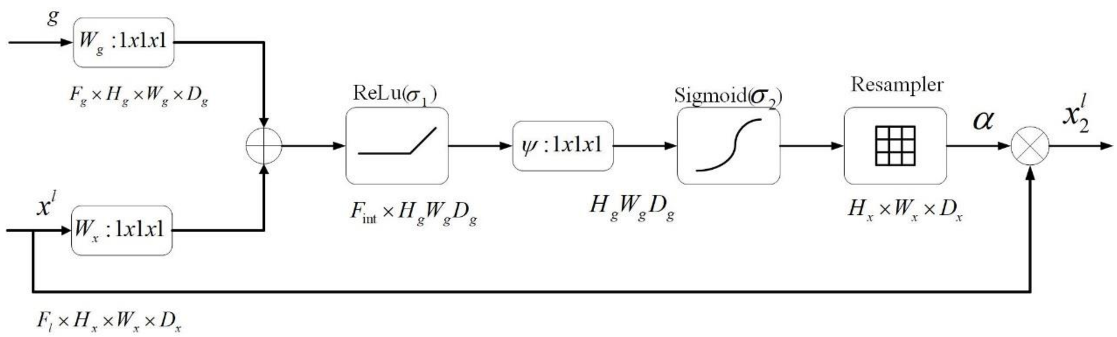



**Figure 4:** Attention gate module

### *3.4. Analysis of network parameters*

In addition, we use batch normalization, 320×320×1 images as input, and initialize weights with truncated normal distribution.The learning rate is set to 1e-5, the loss function is dice (Dice Loss) [11], use adam [12] As an optimizer, ReLU is used as the activation function.

### *3.5. Model performance evaluation metric*

We choose four indicators to evaluate the segmentation accuracy: Dice coefficient (dice similarity coefficient), IOU (intersection over union), sensitivity index (sensitivity) and specificity index (Specificity). They are calculated using a confusion matrix, which is a 2×2 array, including four parameters: false positive (FP), false negative (FN), true positive (TP), and true negative (TN) [13,14]. Dice coefficient (dice similarity coefficient), IOU (intersection over union), Sensitivity index (Sensitivity) and Specificity index (Specificity) are respectively expressed by formulas (1)-(4).

$$Dice = \frac{2*TP}{(TP+FN)+(TP+FP)} \quad (1)$$

$$IOU = \frac{TP}{TP+FN+FP} \quad (2)$$

$$Sensitivity = \frac{TP}{TP+FN} \quad (3)$$

$$Specificity = \frac{TN}{TN+FP} \quad (4)$$

## 4. Experimental results

We tested 123 MRI T2W images of 13 patients and segmented uterine fibroids of different shapes. Figure 5 shows the results of AR-Unet designed to segment uterine fibroids of different shapes, as well as ResNet101-Unet and Attention. -Results of subjective comparison by Unet. From left to right, each column is the original image, true label, Attention-Unet segmentation result, Resnet101-Unet segmentation result, AR-Unet segmentation result. Compared with other methods, AR-Unet has more accurate segmentation of uterine fibroids contours, and has more obvious advantages in image processing of uterine fibroids with more shadow noise and more accurate segmentation. For irregularly shaped uterine fibroids, the details are more accurately segmented. For small uterine fibroids, the effect of segmentation is also ideal.

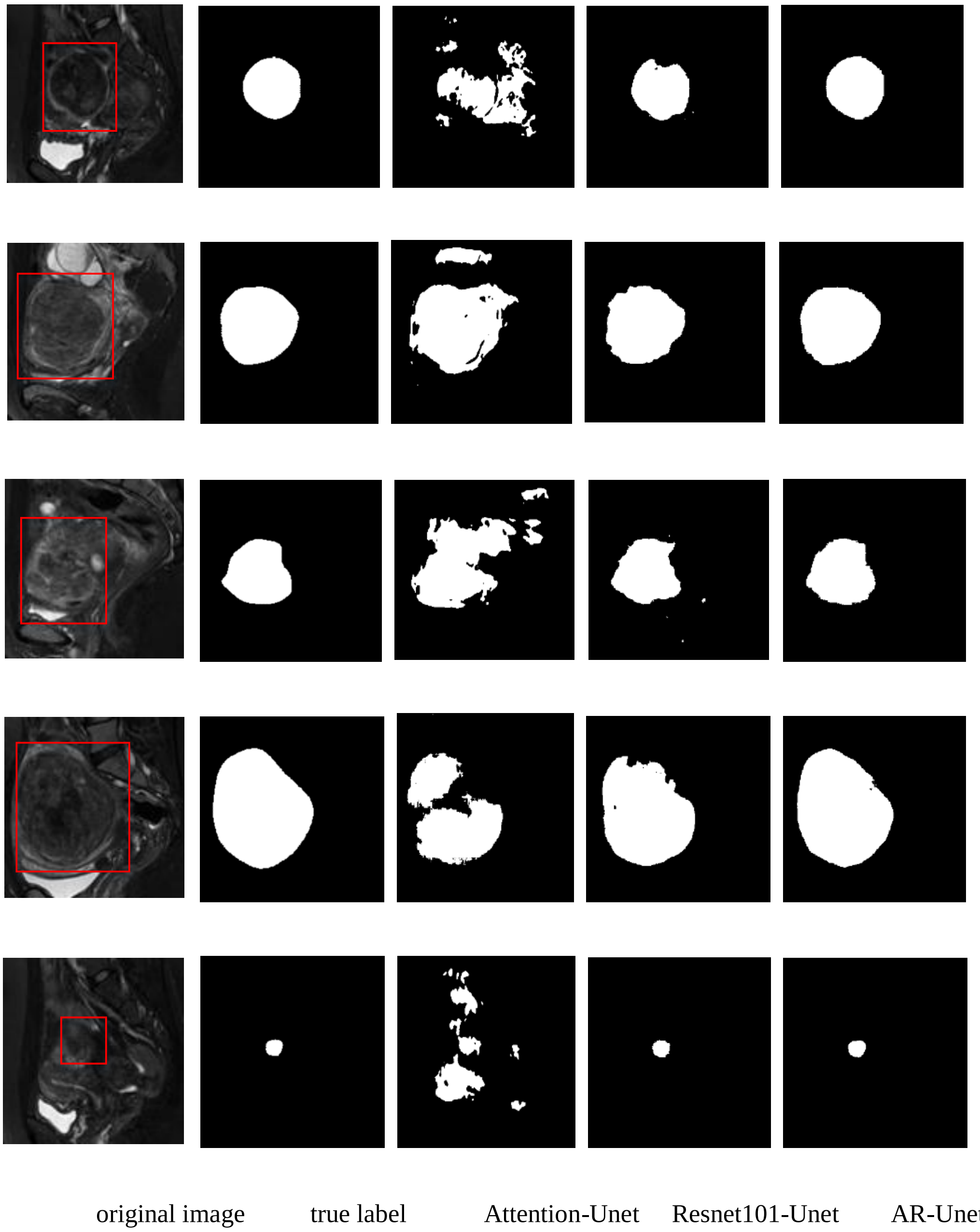



**Figure 5:** Subjective comparison of AR-Unet and ResNet101-Unet, Attention-Unet segmentation results.

Table 1 is AR-Unet's evaluation of the segmentation results of each patient, using Dice, IOU, Sensitivity and Specificity as evaluation indicators. It can be seen from the table that the values of Dice and IOU show high segmentation accuracy. At the same time, the Specificity value is greater than Sensitivity, which proves that the proposed network can correctly detect the uterine fibroids area.

**Table 1:** Comparison of the segmentation results of AR-Unet for each patient

| Dataset | Evaluation index | | | |
|---|---|---|---|---|
| | Dice(%) | IOU(%) | Sensitivity(%) | Specificity(%) |
| 1 | 91.25 | 85.67 | 89.44 | 96.53 |
| 2 | 92.43 | 87.02 | 92.11 | 97.26 |
| 3 | 89.66 | 82.48 | 86.37 | 93.94 |
| 4 | 94.29 | 89.18 | 95.71 | 96.11 |
| 5 | 87.54 | 80.49 | 85.26 | 92.69 |
| 6 | 90.13 | 82.48 | 86.92 | 91.04 |
| 7 | 90.56 | 85.13 | 87.35 | 95.77 |
| 8 | 93.58 | 87.74 | 90.11 | 95.02 |
| 9 | 85.78 | 80.51 | 85.42 | 89.93 |
| 10 | 91.34 | 84.13 | 89.28 | 95.57 |
| 11 | 88.59 | 82.37 | 89.63 | 94.15 |
| 12 | 90.51 | 84.96 | 86.48 | 95.73 |
| 13 | 90.01 | 85.47 | 87.13 | 95.54 |
| Average | **90.44** | **84.43** | **88.55** | **94.56** |

Table 2 is the comparison results of ResNet101-Unet, Attention-Unet and AR-Unet segmentation results in Dice, IOU, Sensitivity and Specificity indicators respectively. It can be seen that AR-Unet is superior to ResNet101-Unet and Attention-Unet in all aspects.

**Table 2:** ResNet101-Unet, Attention Unet and AR-Unet network comparison

| Evaluation index | Network | | |
|---|---|---|---|
| | Attention Unet | ResNet101-Unet | AR-Unet |
| Dice(%) | 67.49 | 86.45 | **90.44** |
| IOU(%) | 60.86 | 80.34 | **84.43** |
| Sensitivity(%) | 65.38 | 83.57 | **88.55** |
| Specificity(%) | 72.63 | 90.33 | **94.56** |

## 5. System

We encapsulated the AR-Unet network into a system and made the interface of the auxiliary segmentation system shown in Figure 6 to assist the doctor to make a judgment. The model button is to select different pre-trained models for different lesion images. For MRI T2 weighted images of uterine fibroids, we use the AR-

Unet network model for segmentation. For the convenience of the doctor, the color correction button can be selected for the correction result, so that the segmentation result is displayed in the original image, where the blue area is the uterine fibroids area.

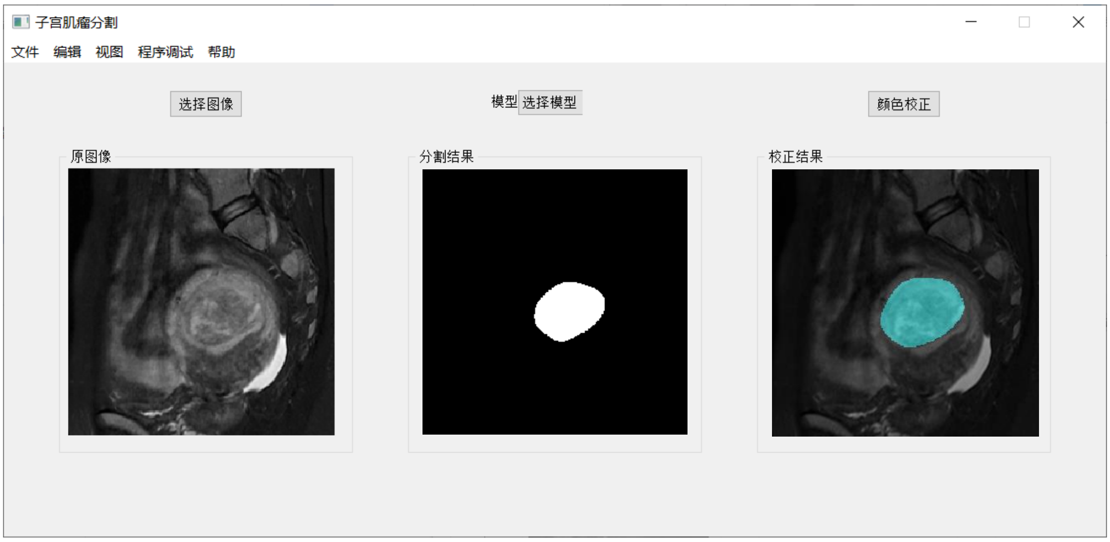



**Figure 6:** Auxiliary segmentation system interface

## 6. Conclusion

The AR-Unet structure designed in this paper has a Dice value of 0.9044 and an IOU value of 0.8443 on the test data set. Compared with ResNet101-Unet and Attention-Unet networks, it has the highest accuracy and the most reliable performance. Experimental results show that the use of deep-level networks for feature extraction, combined with attention mechanisms, has played a substantial role in improving the network. Therefore, AR-Unet can help doctors make more accurate judgments, improve work efficiency and reduce misdiagnosis rate.

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