Abstract—Due to the high resolution of pathological images, the automated semantic segmentation in the medical pathological images has shown greater challenges than that in natural images. Sliding Window method has shown its effect on solving problem caused by the high resolution of whole slide images (WSI). However, owing to its localization, Sliding Window method also suffers from lack of global information. In this paper, a dual input semantic segmentation network based on attention is proposed, in which, one input provides small-scale fine information, the other input provides large-scale coarse information. Compared with single input methods, our method based on dual inputs and attention: DA-RefineNet exhibits a dramatic performance improvement on ICIAR2018 breast cancer segmentation task.

Index Terms—Convolutional neural network, Dual input, Semantic segmentation, Whole-slide image, Attention.

I. INTRODUCTION

Breast cancer is one of the most common cancers among women. In 2012, breast cancer caused more than 500,000 deaths, and 2 million new cases were added[1]. At present, the detection and diagnosis of breast cancer mainly depends on the observation and analysis by pathologists in the pathological section via hematoxylin and eosin staining. This method is subjective, qualitative, and seriously dependent on the professional skill of pathologists. With the development of efficient and stable slicing, staining and imaging techniques, the efficient, accurate and quantitative computer-aided diagnostic algorithms will effectively supplement the shortage of skilled pathologist, and increase the average accuracy of diagnostic greatly. In recent years, from LeNet[2], GoogLeNet[3], to Inception[4], with the improvement of the performance of depth feature extractor, the automatic analysis method of medical image based on deep convolutional neural network is booming. With the observing of features learned from deep neuron networks, it is generally believed that neurons in shallow layers learned the low-level edge or texture features while neurons in deeper layers learned the high-level semantic features. Ronneberger et al first proposed an Encoder-Decoder model named Unet[5] for medical image segmentation. Future works based on Unet such as H-DenseNet[6] and GP-Unet[7] also retained the Encoder-Decoder architecture. This class of models usually contain two parts, named Encoder and Decoder respectively. The Encoder was used to extract high-level semantic features while the Decoder was used to decode segmentation information from the output learned features of Encoder by up-sampling and convolution operations. Moreover, the Encoder and the Decoder can be connected together for feature fusion through an operation named “jump connection”. These UNET-based methods are widely used in natural image segmentation tasks, however, when it comes to segmentation tasks on whole slide images, the single input Unet-based methods will face the problem of small receptive field due to the large size or high dimension of WSI images.

We proposed a dual input encoder-decoder structure named DA-RefineNet, which proved can tackle the above mentioned problem efficiently without high memory consumption.

We found that the same texture structure was labeled different at different locations through observations on the original images and its corresponding split masks(Fig.1). Intuitively, we think this is caused by the differences among the surrounding tissues where they located. In order to make the input image contain surrounding environment information as much as possible, we can increase the size of the input image, however, it will raises a high memory consumption, thus were not considered here. Based on this, we propose a dual-input attention network, here we denoted as DA-Refinenet, which combines fine texture features and coarse semantic features together to allow the network to obtain a large enough receptive field within an acceptable range. In our method, since a large range of images only provide semantic information, there is barely no need to pay much attention to its texture information, so it is down-sampled to accompany with the dimension of another input. Hence we can get enough receptive field under limited memory. Besides, Our method is applicable for but not limited to semantic segmentation, which is a universal idea for other WSI processing problems.

The main contribution of our paper can be summarized as below:

1) Firstly, we proposed a new feature extraction method for WSI image segmentation. The proposed method can extract rough global features and fine local features simultaneously and thus can obtain a much larger receptive field. The proposed method can achieve better performance in terms of accuracy compared with methods that rely on single inputs on the WSI segmentation task.
(2) Secondly, we explored the interaction between rough features and fine features and have the intuition that rough features can assist the fine features for reorganization. Consequently, we proposed a feature fusion mechanism with attention based on the intuition.

(3) Thirdly, we proposed a lightweight feature expression module based on the refine block and the residual connection, which can keep the accuracy while have the number of parameters greatly reduced.

The remain parts of the paper are: In Section II, we give a general introduction to the related works of semantic segmentation on natural and whole slide images. In Section III, we give the detailed information of our proposed methods, which include the model architecture, working scheme and implementation details. Experiment results were demonstrated and analyzed in Section IV, moreover, it also contains a simple introduction to the dataset used in these experiments. Finally, we summarized this work in Section V.

II. RELATED WORK

Recent years have seen more and more powerful functions of the convolutional neural network in tasks such as computer vision[8][9] and natural language processing [10][11][12]. As a basic task of computer vision, semantic segmentation also begins to use deep network methods. With the FCN[13], the encoder-decoder structure shines in the semantic segmentation. For the first time, UNet[5] used this encoder-decoder structure in medical image segmentation tasks and proposed a long jump connection to fuse multi-level features effectively. Badnarrayanan et al, proposed a new encoder-decoder network SegNet[14], which has a pooled structure with coordinates to solve the loss of information in the pooling layer of the encode stage. Zhao et al, by introducing context information in the FCN, proposed a new semantic segmentation network PSPNet[15], which used the spatial pyramid structure to combine the features of different receptive fields for the fusion of multiple levels of semantics. Lin et al, proposed a new module RefineNet[16], which is based on Resnet’s[17] idea of residual connection, which can make full use of the information lost over downsampling to make dense prediction more accurate, And also has a new chained residual pooling capture background context information in an efficient way. Yu et al, proposed a feature discrimination network (DFN)[18] for the inter-class indistinction and intra-class inconsistency in semantic segmentation. The DFN has two module: Smooth Network and Border Network. Smooth Network was designed as U-shaped structure, which can capture context information of different scales and capture the global context through global average pooling, In addition, the Channel Attention Module (CAB) is used to guide the selection of low-level features step by step using high-level features. From the above work, we can see that the key to the semantic segmentation task is the fusion and reorganization of low-level features and high-level features.

In WSI segmentation, sliding windows are currently applied for splitting them into smaller-sized images for semantic segmentation. Two main directions are as follows. One is to use the segmentation of the patch as a classification task. Cruz-Roa et al[19] used a classification network to propose an accurate method for detecting invasive breast cancer with a Dice of 0.7586; Hou et al[20] added the EM algorithm as post-process- sing to the classification network to adaptively combine the patch-level classification results. Korsuk et al[21], added multiscale information to the classification network to improve segmentation accuracy, but they did not explore the relationship between features of different scale and only used a sample feature fusion. This classification-based approach is unscientific and rough, because it gives each patch the same label, which is obviously not very friendly to the edge of the category and the very small part. The other is train a segmentation network end to end, this method is intuitive and scientific. Cruz-Roa et al[22] used deep learning for the whole-slide segmentation task of breast pathology first, and achieved better performance than manual extraction features. Gu,Feng et al[23], proposed a Multi -Resolution networks based on FCN.
for WSI segmentation, however, this work also does not have
any qualitative analysis of the features of different scales, and
does not do too much experimentation on the fusion between
features.

Some work on this dataset is relatively scale. Dong et al.[24]
proposed a simple yet efficient framework Reinforced Auto-
Zoom Net (RAZN). This is the first breast cancer segmentation
network based on reinforcement learning. They designed a
reward module to selectively zoom on the areas that are most
interested in. Kohl et al.[25] only used the Densenet[26] to
do some experiments and see the results, without proposing
an innovative method. Most of the other methods [27][28][29]
also adopted the idea of classification to complete this task. It
can be seen that there is no practical and popular framework
for this task. Therefore, our method based on encoder-decoder
can be trained end to end, and this method is very competitive.

In this paper we adopt Refinenet[16] as the baseline. The
main difference between Refinenet and Unet[5] lies in the
unique block “Refine Block”. The Refine Block is a unique
feature fusion block, which can be divided into three parts.

1) Residual Convolution Unit (RCU). This is a convolu-
tional module based on the residual connection design. Com-
pared with the original Resnet[17], the BN layer is removed,
and the parameter amount is reduced to be used as a feature
extractor.

2) Multi-size fusion. Our task is semantic segmentation,
with the output and the input in the same size, the blocks
except for Block No.4 being dual input, and the two input
in different scales. Thus multi-size fusion is applied for
upsampling and feature fusion.

3) Chain residual pooling(CRP). The module efficiently
fuses features through convolution pooling operations of dif-
ferent window sizes. Through this chained pooling operation,
the receptive field is expanded. At the same time, multi-scale
information is merged through short jump connections, which
let gradient go directly from one module to another.

III. METHODOLOGY

A. Main Frame

Inspired by Unet, we also adopted the encoder-decoder
structure in our work. In order to combine the coarse global
semantic information with the fine local detail information
and increase the receptive field of the network, we use
two independent feature extractors to obtain the high-level
semantic features of the fine image and the coarse image
respectively. Each feature extractor uses four levels of Resnet,
denoted by subscripts 1, 2, 3, and 4, respectively. Each
stage ends with a downsampling process, so that the size of
each level of the feature map is half the size of the feature
of the previous stage, which is beneficial to quickly expand
the receptive field. The extracted features are recombined by
the Attention-Refine(Attn-Refine) Block and then gradually
returned to the original image size. The feature fusion of each
step is a fine image feature recombination performed under
the guidance of the coarse image semantics. We denoted the fine partial image and the rough global image as A and B respectively, moreover, A is part of B. M and L represent the corresponding segmentation result and label mask of image A respectively. Resnet1 and Resnet2 are fine small feature extractor for the pictures A and B. X is the decoding feature of the previous feature layer.

\[
X_A = \text{Resnet1}_1(A) \tag{1}
\]

\[
X_B = \text{Resnet2}_1(B) \tag{2}
\]

for \(i=2,3,4:\)

\[
X_{A,i} = \text{Resnet1}_i(X_{A,i-1}) \tag{3}
\]

\[
X_{B,i} = \text{Resnet2}_i(X_{B,i-1}) \tag{4}
\]

\[
X_3 = \text{Attn}_\text{Refine}_1(X_{A,4}, X_{B,4}) \tag{5}
\]

\[
X_2 = \text{Attn}_\text{Refine}_2(X_{A,3}, X_{B,3}, X_3) \tag{6}
\]

\[
X_1 = \text{Attn}_\text{Refine}_3(X_{A,2}, X_{B,2}, X_2) \tag{7}
\]

\[
M = \text{Attn}_\text{Refine}_4(X_{A,1}, X_{B,1}, X_1) \tag{8}
\]

\[
\text{LOSS} = \text{NLLLoss2d}(M, L) \tag{9}
\]

**B. Attn-Refine Block**

Based on the intuition that coarse images guide the reorganization of fine images features, we add the attention into the network and propose the Attention-Refine Block (Attn-Refine Block) (Fig. 3). To make comparison, we keep other parts unchanged, such as RCU and CRP, which are the same to the RefineNet.

Attention Block is designed to be used for feature fusion, for encoder-decoder structure of single input, the features are \(X_A\) and \(X\), \(X_A\) provides structural information to assist \(X\) for decoding. But for dual input, in addition to \(X_A\) and \(X\), we also have a rough large-size feature \(X_B\). We use the semantic information of \(X_B\) and \(X\) to weight the structural information of \(X_A\) to generate more accurate structural information, thereby increasing the ability to express features. (Fig.4) The working scheme of the proposed Attention Block can be formulated as below:

\[
X_C = \text{Concat}(X_A, X_B, X) \tag{10}
\]

\[
X_W = \text{Residual}(X_C) \tag{11}
\]

\[
Y = X_A \ast X_W + X \tag{12}
\]

Where \(X_A\), \(X_B\) are feature vectors extracted by the feature extractor from images A and B. X is the decoding feature generated by the previous layer Attn-Refine module. Here we use a 1*1 convolution to reduce the feature channels to the original number, and then use Global Average Pooling (GAP) and Sigmoid to generate a one-dimensional weight vector to have a weighted attention on \(X_A\). It is proved very effective to incorporate large scale rough features using the above mentioned scheme. Moreover, the large scale feature only be concatenated as auxiliary information in the feature fusion process and this network structure also allows the proposed model to be well fitted and easy optimized.

In order to explore the relationship between several features, we also proposed several feature fusion schemes for comparison as below. (Fig.5)

1. **Concat:** This scheme just fuse different features together simply by concatenation through the channel dimension, thus an increased number of feature channels will be derived. Moreover, the concatenated features are contributed equally, which is different with the Attention scheme. The computation complexity would increased and thus lead to more difficult optimization.

2. **Add:** The direct addition of the corresponding channels of different features has the lowest in computational complexity, however the relationship among the original channels is destroyed during the addition process, so there are some feature information loss.

3. **Attention:** This method has a certain degree of prior knowledge, which is consistent with the rough large-scale image mentioned in the above as an auxiliary information to promote the reorganization of fine image features.

**C. LW-Attn Block**

From the experiment results which will be demonstrated in the later section, we observed that the proposed method
can achieve comparably high performance. Furthermore to illustrate the effectiveness of our proposed method, we remove some parameter-heavy parts and derived a lightweight version of Attention Block (here we denoted as LW-Attn Block). The experiment result shows that the model weights can be greatly reduced with the accuracy rate almost not affected.

LW-Attn Block (Fig. 6.) is a lightweight feature fusion module based on attention. The parameter quantity is about one-third less than the Attn-Refine block, but hardly any reduction was observed in its accuracy. Compared with Attn-Refine block, the CRP layer is removes from it. Of course, we also turning the RCU stack into a simple residual module: SRB (Fig.7.), which is inspired from the architecture of ResNet [17][30]. The first and the last component are 1*1 convolution layers. We use it to unify the number of channels. The remaining part is a residual block, here we deleted the BN layer and the Relu layer for simplify. This residual connection not only allows the gradient to spread quickly, but also allows multiple features of different scales to be directly fused, thereby increasing the expressive power of the segmentation network.

**D. Evaluation Metrics**

In order to evaluate the performance of our proposed model, we follow previous works [27][28] and choose MIOU, Accuracy and score as the evaluation metric. score is a dedicated indicator for this task.

\[
    h = \sum_{i=1}^{N} \max(|gt_i - 0|, |gt_i - 3|) \ast [1 - (1 - pred_{i,bin})(1 - gt_{i,bin})] 
\]

(13)

\[
    score = 1 - \frac{1}{N} \sum_{i=1}^{N} |pred_i - gt_i|/h 
\]

(14)

Where "pred" is the output predictions on categories (0, 1, 2, 3), "gt" represent the ground truth, and the subscript bin indicates the result of binarization, which means that the real label is 0, then 0, and the others are 1. The indicator score is based on accuracy, but is designed to penalize more pixels away from real values. Note that, in the denominator, the cases in which the prediction and ground truth are both 0 (normal class) are not counted, since these can be seen as true negative cases.

MIOU is the standard measure of accuracy in semantic segmentation. It calculates the IOU for each class, and then averages the IOUs for all categories. And the IOU is:

\[
    IOU = \frac{DR \cap GT}{DR \cup GT} 
\]

(15)

Where DR is the detection result and GT is the ground truth.

**E. Implementation Details**

In this work we use Negative Log Likelihood as the loss criteria for the proposed model. Negative Log Likelihood loss is also called Cross-Entropy loss, which can be writed as:

\[
    NLLLoss2d(t, y) = - \sum_{i=1}^{N} t_i \log y_i 
\]

(16)

where t is one-hot vector for the labels (i=0,1,2,3), respectively, y is softmax output probabilities for the normal, benign, situ and invasive.

We use the SGD[31] optimizer to train our model. Since imagenet pre-training exists in the encoding stage, we set different hyperparameters for the encoder and decoder. The encoder parameter suffix is ENC and the decoder suffix is DEC. At the same time, we divide the training into three steps, and each step have 25 epochs. The initial learning rate of each step are \( LR_{ENC} = [5e^{-4}, 2.5e^{-4}, 4, 1e^{-4}] \), \( LR_{DEC} = [5e^{-3}, 2.5e^{-3}, 1e^{-3}, 3] \), the Momentum is set to 0.9 and WD is 1e-5. Batch size is 12. All code is written by Pytorch. And we use four GTX1080Ti for our training.

We mainly conducted three experiments to evaluate the effectiveness of our proposed model. The first experiment explored the role of the proposed dual-input structure on improving segmentation performance. The second experiment was aimed at exploring the effect of several different feature fusion mechanisms. And the last experiment was meant to derive a lightweight model with segmentation accuracy not decreased.

The training set consists of 3000 patches selected from image 1, 2, 3, 4, 6, 7, 8, and 9. In order to ensure the relative balance of the four categories, we select a total of 2000
patches containing benign or situ. Since that there also exist some normal and invasive samples in these patches, thus we randomly choose another 1000 patches without benign and situ regions. The validation set consists of the 500 relatively balanced patches selected in image10. The test set consists of a total of 3000 patches of all the patches in image5. More detailed information of the dataset can be seen in[32].

We use some data augmentation such as random flip, random crop, and also we normalized the all image to ImageNet dataset. Nowadays, for the segmentation problem of WSI, a strong post-morphological processing is used to optimize the segmentation result, although this can increase the segmentation accuracy but cannot reflect the true performance of the network and the defect of the method. So in order to be able to visually represent the advancement of the method, we have not used any processing and post-processing methods. Although we do not use any post-processing, our method is still competitive compared to other methods.

IV. EXPERIMENTS AND RESULTS

A. ICIAR2018 Dataset

We used the dataset of ICIAR(International Conference on Image Analysis and Recognition) 2018 challenge[32]. The dataset is composed of Hematoxylin and eosin (H&E), stained breast histology microscopy, and whole-slide images. The dataset encompassed a total of 400 microscopy images which were labelled as normal, benign, in situ carcinoma or invasive carcinoma according to the predominant cancer type in each image. The annotation was performed by two medical experts and images with disagreement were discarded. The dataset also contains 10 whole slide images. Whole-slide images are high resolution images containing the entire sampled tissue. In this sense, microscopy images just served as details of the whole-slide images. Because of that, each whole-slide image could have multiple normal, benign, in situ carcinoma and invasive carcinoma regions. The annotation of the whole-slide images was also performed by two medical experts and images with disagreement were discarded. Each image has a corresponding list of labelled coordinates that enclose benign, in situ carcinoma and invasive carcinoma regions (the remaining tissue is considered normal and thus is not relevant for performance evaluation).

Another thing need to mention is that in our work, we have not use the microscopy images for pre-training, which means we employed the whole slide images and microscopy images to train the model simultaneously.

B. The effect of Dual-Input

In this experiment, to evaluate the effect of the proposed dual-input mechanism, and to make the evaluation results more convincing, we adopted several encoder and decoder structure variants. For the feature extractor of different images (the fine small scale image A and the coarse large scale image B), we use three variants of ResNet (50, 101 and 152 respectively) for A and ResNet-50 for B for the consideration of controlling the model parameter amount. For the feature extractor of different images (the fine small scale image A and the coarse large scale image B), we use three variants of ResNet (50, 101 and 152 respectively) for A and ResNet-50 for B for the consideration of controlling the model parameter amount. As for the feature fusion part, we used mode (2) in Fig. 5 for the sake of simplicity. The results are displayed in Table I. In the encoders listed in Table I, Resnet50 means that we used the single input method, and this was to extract the characteristics of image A; Resnet50-50double means that we used the dual input method, and for the fine image and the coarse image, we used two independent Resnet50 as the feature extractor. For the decoder part, we used the two feature fusion modules described in Chapter III. The evaluation indicators, IOU0, IOU1, IOU2, and IOU3, represent the IOU scores of the four categories of normal, benign, situ and invasive cancer, respectively. MIoU represents the average IOU score in the four categories. Also, the loss of the experiment 4 and 5 is displayed (Fig.8).

Form the results we have:

1) The segmentation accuracy of benign and situ are relatively low, which may have some relation with the class imbalance of our dataset. Although we have adopted some techniques to balance different classes, it is inevitable that there will be more normal and invasive cancer than the other two types.

2) According to the four corresponding pairs of comparison experiments, our method based on dual input has brought great improvement than the original method. Especially, the most important indicators of MIOU have increased by 28%, 10%, 18%, 18% respectively.

3) Comparing results in experiments 3, 5, 7, and 9, we found that dual input could reduce the dependence on the feature extractor. Even if we used very shallow encoder and very simple decoder, acceptable results can be obtained. Comparing experiment 3 and 7, we found the results were very similar, which proved that our feature extraction method based on dual-input was efficient, and that we could use the shallow feature extractor to obtain similar results with the deep feature extractor. This has greatly relieved the predicament that most existing methods that merely focus on network depth, which indicates that a good feature extraction structure can make the network achieve better results.

4) Our proposed lightweight network LW-Attn block is very competitive. By observing Experiments 7 and 9, we found
that the results of the LW-Attn block and the original A-Refine Block were basically consistent. But the parameter size of our module was one third of the original.

5) We compared the amount of parameters. Although our approach has led to an increase in the amount of parameters, we can see from Experiment 2 and 5 that we can use smaller parameters in our method to get better results.

6) It can be seen from Fig.8. that our training loss declines more quickly, the model converges faster and the fitting effect is much higher than that in original method. This is because the single input method does not fit well to the situation shown in the box in Fig.1. What the single input network sees is: similar textures are differently labeled. As a result, the loss fluctuates downward, and the convergence values is high.

C. Exploration on different feature fusion schemes

We intuitively believe that rough global features provide auxiliary information for fine local features. This also can be seen as feature recombination. For this reason, we designed this experiment to explore the effects of different feature recombination schemes. (see Fig.5).

Experiments were done with ResNet50_50_double, ResNet101_50_double for the encoder and Refine block for the decoder. The experimental results are shown in Table II. 101_50_1 indicates that Resnet101 was used as the feature extractor for fine small-scale images, Resnet50 was used as the feature extractor for rough large-size images, and (1) in Figure 5 was used as the feature fusion module.

From the results we have: a good feature fusion structure can reduce the dependence of the network model on the feature extractor. Compared with resnet101, the feature extraction capacity of resnet50 is relatively poor. When we used the feature fusion structure such as Add and Concat, similar conclusion can be derived from observing the corresponding results. But when we used the attention-based feature fusion structure, the result of resnet50 was better, which means that the coarse global information is indeed a priori of the fine local features, and that, by using Attention-based feature fusion, we can not only accelerate the convergence, but also get better expressed features. This not only reduces our reliance on hardware, but also saves time and provides a practical idea for real-time segmentation.

D. Additional Experiment

We proved that the performance improvement was derived from the proposed dual inputs scheme other than the increase of the parameter quantity, which further proved the superiority of our method. We compared our method with the multi-size dual input. Multi-size dual input refers to the input of two images of the same content but different sizes. We use three encoding structures resnet50, 101, 152, and Refine Block as the decoders. The results are shown in Table III.

From the results we can see:

1) Compared with single input, Multi-size dual input still brings a big improvement in performance. This shows that the input of multi-size has a great effect on the semantic segmentation task. Because the target of our segmentation is irrelevant to the size of images, we hope that our segmentation network will be able to extract as many features of constant scale as possible. And this multi-size dual input just promotes the extraction of scale-invariant features of the network.

2) The IOU0 and IOU3 of Multi-size dual input are the same as ours basically. But the IOU1 and IOU2 are lower. This means the method of Multi-size of dual input has limitations for difficult segmentation tasks and shows that the multi-size method is as small as the single-input method and cannot use global information to optimize the results.

3) Although we only used the feature fusion method of Add, this is enough to show the superiority of our method. In the case where the overall is better than Multi-size dual inputs, the indicators of IOU1 and IOU2 are greatly improved, which shows the advancement of our method is not due to the increase of parameter numbers.

E. Visualization Results

We also present the visual segmentation results for better illustration of the effectiveness of the proposed mode. As shown in Fig. 9, for the reason that we did not applied any post-processing techniques, thus lead to some blur and noise. Although there are some unsatisfying results, but these results can reflect some shortcomings of the whole slide image segmentation problem, which may be solved in future works. By observing the segmentation results of the third row, the fourth row of single input and the last row of multisize input, we can see that there exist a lot of red noise on the black background, which means the network tend to divide the normal into benign. This is consistent with the phenomenon we mentioned in the motivation at the beginning of the paper. Due to the lack of global information, some parts of the training data with similar textures and normal areas are likely to be labelled as benign, which can mislead the network, causing the network to be inferior for benign and normal, resulting in misclassification. The segmentation results based on the dual-input network of row 5 and 6 corresponding to this have a relatively clean background. We also compare the feature fusion method based on Add in row 5 and the feature fusion method based on Attention in row 6. Compared to the simple addition of two features, we found that the method of using large-scale coarse semantic information to participate in small-scale fine texture feature reorganization has achieved better results, especially for test image 5.

All methods predict some normal areas on the right side of image 5 as benign, we have observed the original image in
Fig. 9. Visual segmentation results of image 5(left) and image 1(right). The first and the second row represent the original image and its corresponding label image respectively. The third and forth row give the segmentation results of single input with ResNet-50 and ResNet-101 respectively. The fifth row and the sixth row demonstrate the segmentation result of dual inputs of ResNet101-50 with feature fusion scheme "Add" and "Attention" respectively. The last row showed the results of multi-size dual inputs.
TABLE I
THE RESULTS OF THE DOUBLE INPUT

| encoder        | decoder       | IOU0  | IOU1  | IOU2  | IOU3  | MIOU | Accuracy | Score | Model size | Number |
|----------------|---------------|-------|-------|-------|-------|------|----------|-------|------------|--------|
| U-net          | U-net         | 45.5  | 25.0  | 20.1  | 50.2  | 31.2 | 57.2     | 49.1  | 150M       | 1      |
| Resnet50       | Attn-Refine block | 60.5  | 28.0  | 21.8  | 55.0  | 36.2 | 67.1     | 58.8  | 334M       | 2      |
| Resnet50_50double | Attn-Refine block | 55.3  | 32.9  | 37.1  | 58.6  | 45.9 | 75.1     | 71.1  | 441M       | 3      |
| Resnet101      | Attn-Refine block | 58.5  | 22.3  | 29.8  | 58.1  | 42.2 | 73.8     | 69.0  | 417M       | 4      |
| Resnet101_50double | Attn-Refine block | 58.0  | 34.5  | 38.9  | 61.4  | 46.5 | 75.1     | 71.6  | 517M       | 5      |
| Resnet50       | Attn-Refine block | 59.0  | 27.7  | 28.3  | 52.5  | 39.7 | 72.7     | 69.7  | 480M       | 6      |
| Resnet152      | Attn-Refine block | 59.5  | 38.1  | 28.8  | 60.9  | 46.8 | 75.5     | 71.5  | 580M       | 7      |
| Resnet152_50double | Attn-Refine block | 57.8  | 21.2  | 27.8  | 54.4  | 40.3 | 69.4     | 62.3  | 250M       | 8      |
| Resnet152      | LW-Attn block | 57.0  | 36.9  | 32.8  | 60.0  | 46.5 | 73.9     | 68.8  | 350M       | 9      |

TABLE II
THE RESULTS OF THE FEATURE FUSION

| Experiment number | IOU0  | IOU1  | IOU2  | IOU3  | MIOU | Accuracy | Score |
|-------------------|-------|-------|-------|-------|------|----------|-------|
| 50_50_1           | 60.1  | 38.9  | 39.2  | 58.3  | 48.9 | 75.7     | 71.5  |
| 50_50_2           | 55.3  | 32.9  | 37.1  | 58.6  | 45.9 | 75.1     | 71.1  |
| 50_50_3           | 61.1  | 40.9  | 39.4  | 62.3  | 51.0 | 76.4     | 72.0  |
| 101_50_1          | 58.3  | 36.6  | 42.0  | 60.0  | 47.8 | 74.4     | 71.9  |
| 101_50_2          | 58.0  | 34.5  | 38.9  | 61.4  | 46.5 | 75.1     | 71.6  |
| 101_50_3          | 59.3  | 36.6  | 44.0  | 59.7  | 49.9 | 74.8     | 72.1  |

TABLE III
THE RESULTS OF THE ADDITIONAL EXPERIMENT

| input                 | encoder        | IOU0  | IOU1  | IOU2  | IOU3  | MIOU | Accuracy | Score |
|-----------------------|---------------|-------|-------|-------|-------|------|----------|-------|
| Multi-size dual input | Resnet50_50   | 60.9  | 24.2  | 31.1  | 63.1  | 44.8 | 74.1     | 71.2  |
|                       | Resnet101_50  | 59.1  | 28.4  | 33.0  | 62.9  | 44.4 | 73.7     | 69.9  |
|                       | Resnet152_50  | 60.4  | 25.3  | 31.2  | 61.8  | 44.7 | 74.9     | 71.1  |
|                       | Resnet50_50   | 55.3  | 32.9  | 37.1  | 58.6  | 45.9 | 75.1     | 71.1  |
| ours                  | Resnet101_50  | 58.0  | 34.5  | 38.9  | 61.4  | 46.5 | 75.1     | 71.6  |
|                       | Resnet152_50  | 59.5  | 38.1  | 28.8  | 60.9  | 46.8 | 75.5     | 71.5  |

detail, and found that this part of the texture was indeed very different from the texture of other normal areas, so we sought help from experts, and were informed that there should be errors in the labels corresponding to the original data, which further explains the reason for some noisy unsatisfying results and the advancement of our method.

V. CONCLUSION

In this paper, we propose a dual-input whole-slide breast image semantic segmentation framework based on attention. Using coarse global features as auxiliary information to promote fine local feature reorganization is the idea of the proposed method, which includes the feature extraction and feature fusion schemes, was derived from the human intuition for solving segmentation tasks. The proposed method can give insight and provide a general framework for future works on WSI segmentation. Moreover, we also proposed a lightweight version feature fusion model named LW-Attn Block, which can achieve comparable performance while with much less model parameters. When the parameter quantity reduces by one-third, the segmentation accuracy is basically unchanged, which can reflect advancement of our method.

At the same time, we also compare the influence of several different feature fusion methods on our network, indicating that the coarse global information can be used as a priori of fine local information to guide its feature reorganization, thus accelerating network convergence and improving network expression ability. This attention-based approach reduces the network’s dependence on feature extractor depth to a certain extent. We can use the shallower feature extraction network to get better results, which not only reduces the model size, but also gives us a lot of inspiration: Network performance is not only dependent on deep feature extractors, but correct prior knowledge and graceful feature fusion are the key factors that determining network performance.

In the future work, much further studies can be done to explore the generality of the proposed method on other WSI related tasks such as survival prediction, gastric cancer detection, and pancreas segmentation.

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