CONIC 2022 Solution

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Abstract—Nuclei segmentation and classification has been a challenge due to the high inter-class similarity and intra-class variability. Thus, a large-scale annotation and a specially-designed algorithm are needed to solve this problem. Lizard is therefore a great promotion in this area, containing around half a million nuclei annotated. In this paper, we propose a two-stage pipeline used in the CoNIC competition, which achieves much better results than the baseline method. We adopt a similar model as the original baseline method: HoVerNet, as the segmentation model and then develop a new classification model to fine-tune the classification results. Code for this method will be made public soon.

I. INTRODUCTION

Nuclei segmentation and classification is of vital importance in computational pathology. Annotating nuclei datasets is a high-cost and time-consuming task, as it requires specific domain knowledge and large efforts. Luckily, a large-scale annotated dataset, Lizard [1], has been announced public recently. It segments and classifies the nuclei into 6 classes: neutrophil, epithelial, lymphocyte, plasma, eosinophil, and connective. Many segmentation and classification methods can be applied in this problem, e.g. Mask RCNN [2]. However, these common computer vision models tend to perform worse than U-Net based methods in nucleus segmentation and classification because nuclei can be very small and crowded. Thus, we follow HoVerNet [4] and adopt U-Net structures in nucleus segmentation. As HoVerNet uses pixel voting of the type map to decide the final instance type, which is sometimes lack of accuracy especially when only several pixels belong to the instance and they don’t agree with each other. Thus, in this paper, we propose a new two-stage method that combines HoVerNet (as the segmentation and rough classification part) and a new classification model (as the fine-tune classification part).

II. METHOD

To solve the problem in the CoNIC competition [5], we adopt a two-stage pipeline to segment and classify the nuclei in H&E patches. As the baseline, HoVer-Net, can perform well in segmentation, we simply add another classification module to further fine-tune the classification results. The pipeline of our framework is shown is Figure 1.

A. Stage-one: segmentation

After careful comparison with other methods, we found that the baseline method: HoVer-Net [4] can perform well on the segmentation task. Thus, we adopt a similar model as HoVer-Net, by changing the backbone of ResNet50 [6] to Resnext50 [7].

B. Stage-two: classification

To further fine-tune the classification results, we apply a second stage focusing on classification. We crop the instances by the bounding boxes of the predicted instance masks. Besides the input image, we also concatenate the predicted type probabilities and the mask. We concatenate all the inputs by the channel dimension and resize the concatenated tensor to a desired input size, which in our case, is 224. We then apply a Resnet50 model as a classification model and use the ground-truth type as a supervision. Each training batch contains items from a balanced sampling of different classes to avoid the effects of the uneven class sampling. We use this classification model instead of the original pixel voting method of HoVer-Net to further fine-tune the classification results.

III. TRAINING DETAILS

We tried the de-facto detection methods like Mask RCNN, but they do not perform as good as the U-Net like method (HoVer-Net). Thus, following HoVerNet, we apply a segmentation model with one encoder branch and three decoder branches. After careful experiments, we found that there is no much difference between training 2 phases (freeze the encoder in the first phase and unfreeze it in the second phase) and training one phase alone. Thus, we simply train the model with only one phase for 50 epochs. The learning rate is set as 1e-4 at first and decays by γ of 0.1 for every 20 epochs.

For the classification model, we use a simple resnet50 [6] with 7 output types. We train the model for 20 epochs with the Adam optimizer. Learning rate is set as 1e-3 at first and decays by γ of 0.1 for every 8 epochs.

We use typical augmentation techniques in pathology images as horizontal flips, vertical flips, random 90 degree rotations, transposes, small-scale color jitter, Guassian blur, and median blur in training. In evaluation, we use test-time augmentation as horizontal flips and vertical flips to improve the performance.

We split the training dataset into five folders by their original domains, which are DigestPath, CRAG [8], GlaS [9], CoNSeP [4] and PanNuke [10]. Each time, we train with four folders and valid the model on the other. We tried different
Fig. 1: Pipeline of our two-stage framework. In the first stage, we follow HoVer-Net in three decoders predicting the foreground/background, horizontal/vertical distance, and the types for each pixel. We then use the same post-process function as HoVer-Net to get the instance segmentation. We then fine-tune the classification results in the second stage by a simple Resnet50. We crop the image and the corresponding probability map by the nuclei bounding boxes and resize them to the desired input size of ResNet50. We also concatenate the mask of the nuclei to high-light the nuclei shape. The output of the classification model is the prediction for the 7 classes and we supervise them with the ground-truth label. Results show that this fine-tuning classification model works better than the original pixel voting module on all the splits.

| PanNuke | GlaS | Preliminary Test |
|---------|------|------------------|
| mP Q+   | R^2  | mP Q+           |
| Baseline | 0.4582 | 0.6953 | 0.3755 | 0.1307 | 0.2956 | -0.4280 |
| Ours    | 0.5088 | 0.8023 | 0.4182 | 0.5015 | 0.3426 | 0.0512 |

TABLE I: Table for comparison with the baseline. Results show that though not high enough to rank at the top, our framework still consistently out-performs the baseline method.

learning rate schemes and augmentation tests and picked only the ones that improve the performances on all the folders.

IV. RESULTS

We achieve good validation results, though the performance is not good enough on hard cases in the preliminary test phase. We show the validation results on two folds: Glas and PanNuke along with the preliminary test dataset in Table I. Note that we did not use any test-time augmentation or model ensambling in validating on validation datasets as PanNuke or GlaS. Though not as high as other methods at the top of the leaderboards on the difficult patches in the preliminary fold, we think our method is still very competitive and can achieve a similar score if the test data is general enough.

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