HIERARCHICAL FRAMEWORK FOR BREAST CANCER STAGE CLASSIFICATION WITH HISTOPATHOLOGY IMAGES

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ABSTRACT

The pathologic N-stage (pN-stage) prediction can tell whether cancer has spread to the regional lymph nodes. However, this prediction needs analysis on whole-slide images which usually are very huge and consume too much time to detect the tumor for pathologist. In this paper, we introduce the deep learning methods recent years in computer vision into tumor detection and propose an automated hierarchical and ensemble framework to predict patience's pN-stage.

Index Terms—GoogLeNet, Patch classification, Random Forest, hard example mining, Metastasis Detection

1. INTRODUCTION

The TNM system [1] is widely accepted to classify the extent of cancer spread in patient. The pN-stage in this system shows the presence of metastases in lymph nodes which has important implications for breast cancer patients. However, detection of tumor by human is time consuming and subjective. Automated detection and classification procedure can reduce the workload and gain objective results.

Camelyon17 [2] is a challenge that using whole-slide image (WSI) with pixels annotated. The main task of this challenge is to determine the pathologic N-stage for every patient in the test dataset which means whether the cancer has spread to the regional lymph nodes.

Deep learning is a popular method in computer vision. It can learn a representation of image from large data with which classifier can distinguish the category easily. Our work is using deep learning method on whole-slide images and classify each slide into four categories: Normal, Isolated tumor cells (ITC), Micro-metastases or Macro-metastases, and then predict the patience's pN-stage according to the given rules.

Our main contributions on this task are (1) we make morphological operation, dilation [3], on the extracted tissue region to raise the recall rate for the color on the edge is light. (2) we filter possible noise data in positive patches with a small classification model. (3) we not only train one stage classifier for patches but also make hard example mining [4] to generate training dataset for the second stage classifier and at last combining the two stage results together for the final result.

2. METHODS

In this section, we introduce a hierarchical and ensemble framework to deal with the whole slide image of patient's histological lymph node for pN-stage prediction. Hierarchy makes the system efficient and ensemble makes it robust. We use two level models to predict the patient's pN-stage hierarchically, and integrate two training period models with combination several kinds of image augmentation results to gain robustness. Figure 1 shows the complete process of our framework and we will discuss it in detail in this section.

2.1. Tissue Region Extraction

A whole slide image is usually huge while the tissue regions are only parts of it. In order to focus on the tissue regions and accelerate processing, we use Otsu [5] threshold method to extract the tissue regions. Otsu method can give us the threshold which used to binarize image according to the pixel statistics between foreground and background. However, segmentation result from Otsu method is not as good as we expected. As is shown on the first image in Figure 1, we found that hematoxylin and eosin (H&E) stained color on the edge of tissue region is light so these regions tends be missing while segmentation. In order to recall these areas, we firstly find the contours of the tissue regions and seek the connected domain [6], and then dilate the connected domain. We use the dilated result as segmented tissue region.

The second image in Figure 1 is an example of extracted tissue region result.

2.2. Patch-Level Model

2.2.1. Patch division

In order to gain fine-grained features, we divide the tissue regions on WSI into lots of 256*256 patches with stride of 128. We label a patch as tumor if over 75% pixels in the patch are annotated as a tumor. With these patches, we gain enough samples to train convolution neural network [7] (CNN) for tumor pattern recognition.

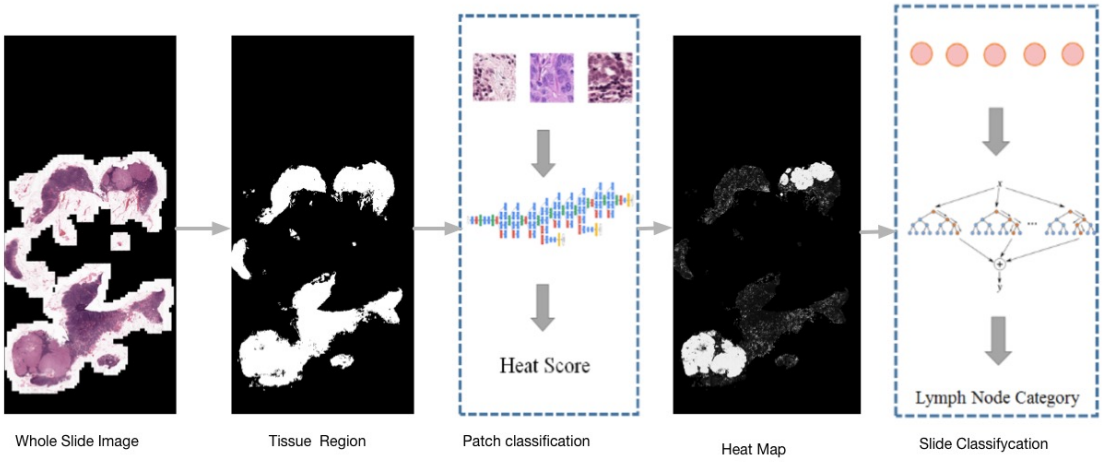

Fig. 1 Complete workflow of our framework on pN-stage prediction

2.2.2. Data selection and augmentation

In the consideration of the balance of performance and speed, we choose GoogLeNet [8] as the patch classifier. During training period, we sample the same number of tumor/normal patches where patches are sampled from each slide with uniform distribution. To combat with the variety of hematoxylin and eosin (H&E) stained color because of chemical preparation difference per slide, extensive color augmentation is performed by applying random hue, saturation, brightness, and contrast. Since the classes of histopathology image exhibit rotational symmetry, we include data augmentation by randomly rotating over angles 0, 90, 180 and 270 degrees, and random left-right flipping.

2.2.3. Model ensemble

First, we train a patch classification model with high confidence data. Then possible noise data in patch level train data, especially the positive patches, are filtered with the model. However, GoogLeNet can only achieve 97.5% accuracy on these training data. In order to enhance the model's classification ability, we do hard example mining on the training data using the first stage classifier. We combine the original model and enhanced model together by averaging the final result of each CNN model as the final probability of this patch to be tumor. With this method, our model gain 1.7% improvement.

The third image in Figure 1 shows the procedure of patch-level classification.

2.3. Slide-level Model

2.3.1. Feature extraction

With the output of patch-level model, we can get each slide's probability heat map. In detail, we use a threshold of $t = 0.75$ to segment the heat map and get the Region of Interest (ROI). We seek the connected domain of these ROIs, and then extract the geometric features from this connected domain, such as axis, area and statistical features such average and max value in this ROI.

2.3.3. Slide classification

Slide-level classification can help to determine the patient' pN-stage. We use 42 features in total to represent the slide. We choose an ensemble classifier, random forest [9] [10], to train slide-level model for its good performance in classification [11]. With these features from heat maps and the random forest classifier, we classify the slides into four classes (Normal, ITC, Micro, Macro) and then predict each patient's pN-stage by the all his lymph node slide categories according to the given rules.

The fourth image in Figure 1 shows an example of heat map and the fifth image shows the procedure of slide-level prediction with random forest.

3. EXPERIMENTS

In this section, we will discuss our dataset arrangement for two levels training and three levels testing. We will describe our experiment setup in detail and the scores we achieved in each step.

3.1. Dataset arrangement

For patch-level classifier training, we use all WSIs with region annotations from Camelyon16 [12] and Camelyon17. In detail, we use 400 WSIs from Camelyon16 and 100 WSIs

from Camelyon17 and divide them into patches. The patches used on training and testing is 10:1 respectively.
For slide-level classifier training, we use the 500 slides from Camelyon17 with 5-folder cross validation.
For patient-level prediction, we use the left 500 WSIs as test set.

3.2. Experiment Setup

To do this experiment, we use Caffe [13] framework and GoogLeNet with initial parameters from ImageNet pretrained model to speed up convergence. We train our model on four NVIDIA Tesla P100 GPUs using SGD [15] optimizer with step decay [16] for about 12 hours. We use a big batch size of 256 when training to gain stability of loss curve.

3.3. Results

Table 1. Three-level scores

Stage	Score
Patch level Accuracy	0.992
Slide level Accuracy	0.89

With the ensemble of two stages CNN, we achieved 98.5% accuracy on our test patches. With the 42 features from the slide heat maps and the random forest classifier, we achieved 89.0% accuracy on slide-level classification with 5-folder cross validation.

4. CONCLUSION AND PROSPECT

In the paper, we introduce a hierarchical framework to predict patient's pN-stage from metastasis slides. Our method is efficient and effective and perform well on Camelyon17 dataset. For further work, we will try deeper network, such as ResNet101 [17] for patch-level model training, try more geometrical and statistical features for slide-level model training.

5. REFERENCES

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