CAMELYON CHALLENGE:THE TNM CLASSIFICATION

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ABSTRACT

In this paper we explained the framework which detect pN-stage of breast cancer in WSIs. We used ResNet-50 for detecting the tumor cells and for evaluating the expansion of cancer regions in WSI. Our model is able to directly predict segmentation of tumor regions. The proposed network is evaluated on the Camelyon17 benchmark, where we obtain the state-of-the-art results.

Index Terms— One, two, three, four, five

1. INTRODUCTION

This challenge will focus on the detection and classification of breast cancer metastases in lymph nodes. Lymph nodes are small glands that filter lymph, the fluid that circulates through the lymphatic system. The lymph nodes in the axilla are the first place breast cancer is likely to spread. Metastatic involvement of lymph nodes is one of the most important prognostic factors in breast cancer. Prognosis is poorer when cancer has spread to the lymph nodes. This is why lymph nodes are surgically removed and examined microscopically. However, the diagnostic procedure for pathologists is tedious and time-consuming. But most importantly, small metastases are very difficult to detect and sometimes they are missed.

The task in Camelyon17 challenge is to determine a pNstage for every patient in the test dataset. To compose a Pathologic lymph node classification, the number of positive lymph nodes are counted. First, the whole-slide images (WSI) of histological slides offer available material to detect the regions of breast cancer. Then according to the detection results of 5 slides every patient, there are three categories of lymph node metastasis each identity including macro-metastases (Macro), micro-metastases(Micro), isolated tumour cells (ITC). Further, based on categories of each patient, pathologic lymph node classification (pN-stage) are divided into the following conditions, namely, no micro-metastases or macro-metastases or ITCs found (pN0), only ITCs found(pN0(i+)), micro-metastases found but no macro-metastases found(pN1mi), metastases found in 1C3 lymph nodes(pN1), metastases found in 4C9 lymph nodes(pN2).

Past work in the literature has been dominated by approaches that pose brain tumor segmentation as the problem of sematic segmentation, which produces dense classi?cation at the pixel level. Generally, hand-crafted features are designed by incorporating with a classi?er learned separately, where the classi?er dose not impact the nature of the designed features. Recent deep convolutional.neural networks (CNNs) have been applied to this task by advancing feature extraction. These approaches compute deep, hieratical and learned features from brain MRIs, allowing the features to be learned jointly and collaboratively with a integrated classi?er. This results in more meaningful features that lead to the state-of-the-art performance.

We propose a new network module capable of aggregating rich ?nescale spatio-temporal features over multiple convolutional layers.

2. METHODOLOGY

2.1. Local Network

Local Network has four convolutional blocks, with down-sample factors and channel numbers of32,64,128,256, as shown in Fig. 1. The proposed local network is applied to each convolutional block, and encodes high-level context information in both spatial and temporal domains recursively, from the higher layers to the lower ones. We design an adaptive layer which is connected to the output of each convolutional block. The adaptive layer reshapes the convolutional maps.Convolutional features are fused recursively from the top convolutional block to the bottom one, where element-wise summation is used, with an 2 up-sample operation implemented on the lower-resolution maps. This results in 128-channel local convolutional maps in the last re?ned convolutional layer, where each convolutional maps have a same shape with the input volume. The ?nal prediction is computed on the 128D features at each location of the features maps. We adopt 111 kernels for all adaptive layers for simplicity, but more advanced con?gurations, such as non-local operation, dilated convolutions, or inception architecture, are readily applicable, and has the potential to improve the performance.

2.2. Unsupervised Classification for Lymph Node

After detecting the metastases regions and isolated tumor cells (itcs) in slide, we need to classify the WSI into four classes. The negative class does not have any itc or metastases. The

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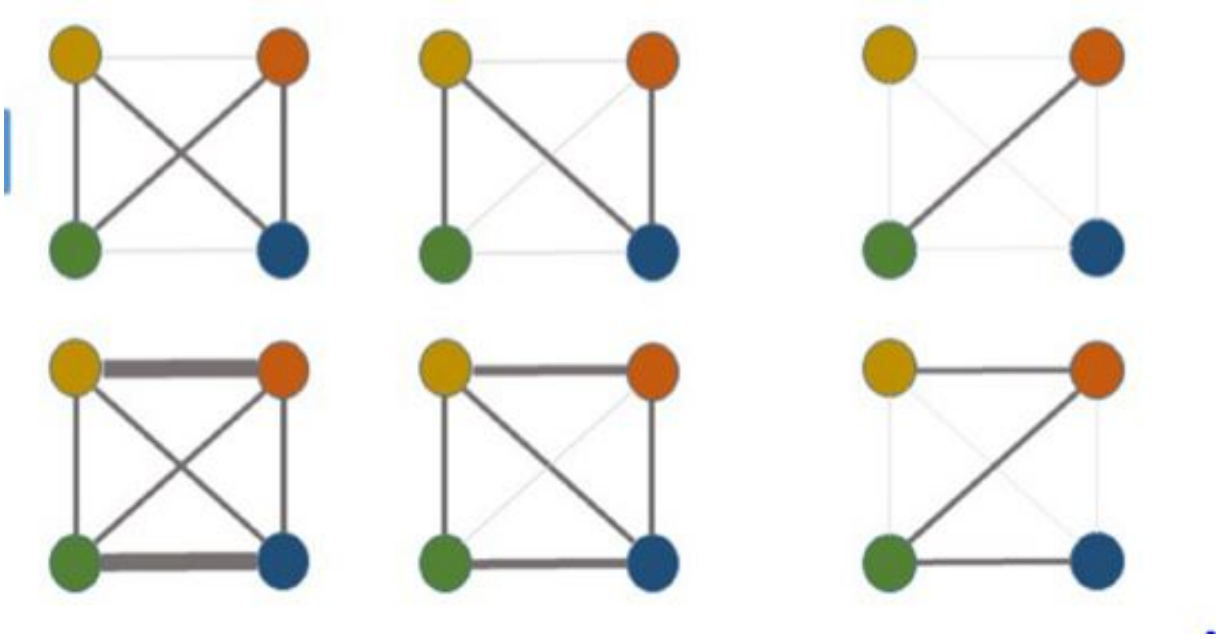

Fig. 1. Overview of our proposed local network.

slides in itc class have small tumor cell blobs with less than 0.2 mm axis length or less than 200 cells. The metastases with greater size or cell number than what is defined for itc, account for micro metastases which have less than 2mm major axis length.

Consequently, the metastases with major axis length greater than 2 mm account for macro class. For estimating the major axis of the tumor blobs, we fit an ellipse to each individual blobs and we measure the major axis of the ellipse and the diameter of a circle with the same area as the region. According these two scaler, we initially label the tumor blobs. Because apart from the above definition the distribution of the tumor blobs in WSI is important for considering them as separate or a unified big blob, we need to consider some clustering concept for classifying between itc and micro or between itc and macro classes. For this purpose, we used density-based algorithm for discovering clusters.

3. EXPERIMENTS

3.1. Data

There are two kinds of data.Lesion-level training data.Lesion-level annotations are also provided for 10 training slides from every medical centre within CAMELYON17 (50 annotated slides total).In this set the micro and macro metastases are annotated exhaustively. Note however, ITCs are not annotated exhaustively.Patient-level training data:For each of the 5 data sources we provide slides that are organised by patient.Each patient is labelled with a pN-stage.Patients consist of 5 lymph nodes.Every slide holds sections of just 1 lymph node.

3.2. Experiment Results

The evaluation of result in Camelyon17 challenge are the five class quadratic weighted kappa where the classes are the pN-stages.

4. CONCLUSION

In this paper, we propose a framework to predict a whole slide image mask by patch-level classification.we proposed a local net that directly aggregates both local details and spatial-temporal context information. We introduced a new training strategy that incorporates curriculum learning, volumetric data augmentation, allowing for a better generalization of the trained model.the network can only learn little information from the image patch, resulting the limitation of accuracy. Furthermore, the similarity of itc, micro and macro metastases increase the difficult of slide level classification.The Local Net obtained the state-of-the-art performance on the CAMELYON17 benchmark.

5. CITATIONS AND REFERENCES

6. REFERENCES

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