WHOLE SLIDE IMAGE CLASSIFICATION VIA ITERATIVE PATCH LABELLING

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Overview

In the study of Whole Slide Pathology Images (WSI), the recognization of discriminative patches, which carry the diagnostic information, plays an important role in the WSI classification tasks. In this study, we propose an iterative patch labelling algorithm based on the Convolutional Neural Network (CNN), to distinguish the discriminative patches from the non-discriminative ones and finally use the discriminative ones to achieve WSI-classification. Our method is evaluated on the MICCAI 2015 Challenge Dataset, and shows a large improvement over the baseline approaches.

Challenges and Significance

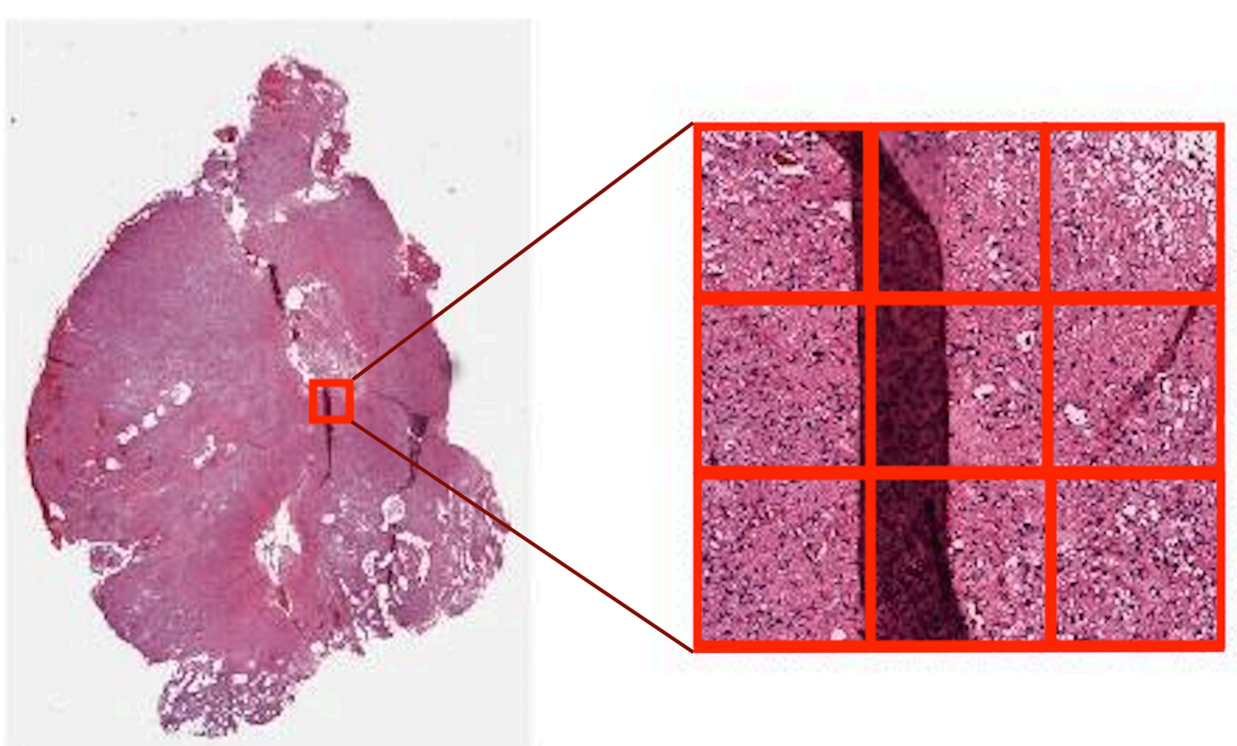


Fig. 1. Patches of size *500 by 500* extracted from a brain WSI of size *28500 by 19500*, at 40X resolution scale.

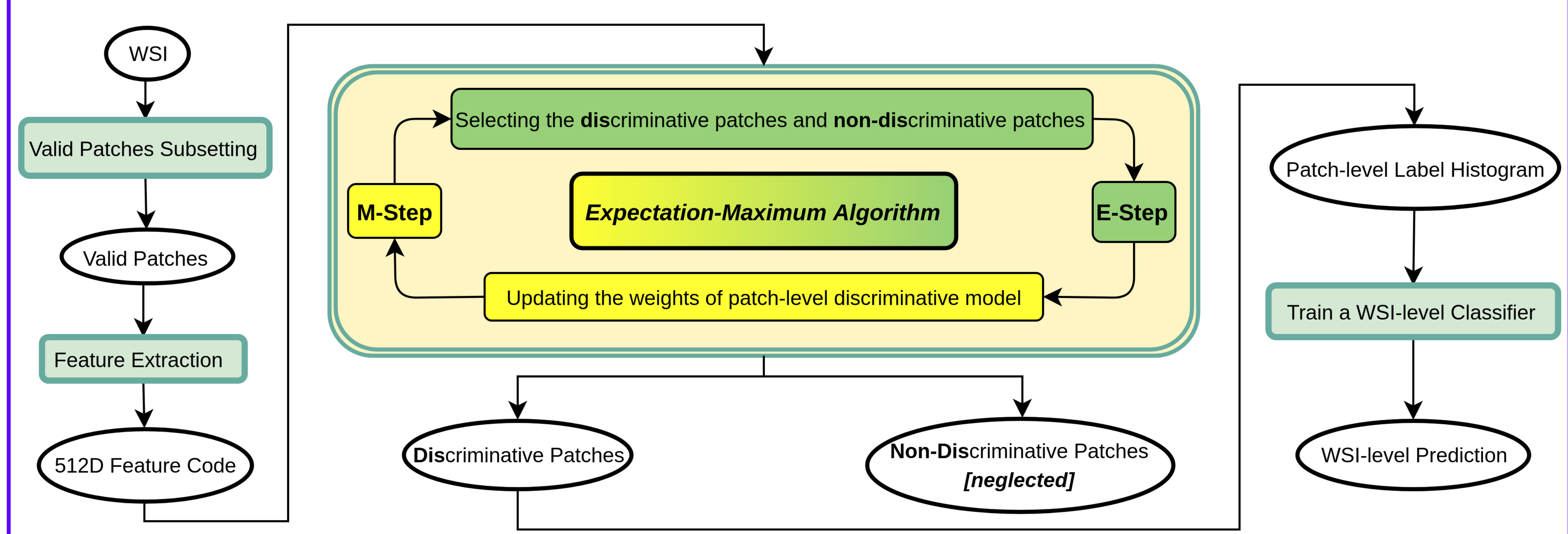
Challenges:

1. The gigapixel WSI leads to a high computational cost.
2. The datasets typically only provide image-level labels.
3. The patches carrying diagnostic information merely take a small proportion of the WSI to be analyzed.

Significance:

An early and accurate classification of brain canner is of significance to increase its survival rate. With the discriminative patches recognized and annotated by the algorithm, a more reliable and explainable result can be produced, which is valuable for the pathologists to reach a final diagnosis.

Methods: (a) Overall Framework



Methods: (b) EM-based Iterative Patch Labelling Algorithm

Algorithm 1 Iterative Patch Labelling Algorithm

procedure
Initialize discriminative model D
Assign all patches X with WSI-level labels
while convergence C is not reached **do**
[M-step]
Use X and their current labels L to train D
[E-step]
Use D to calculate $P(X, K)$ for each X with class K
Generate the possibility maps *PMap* for each WSI
Apply Gaussian Smoothing on *PMap*
Apply Thresholding Scheme on *PMap*
Update L
Save D architecture and its weights

- **Discriminative model D architecture:**

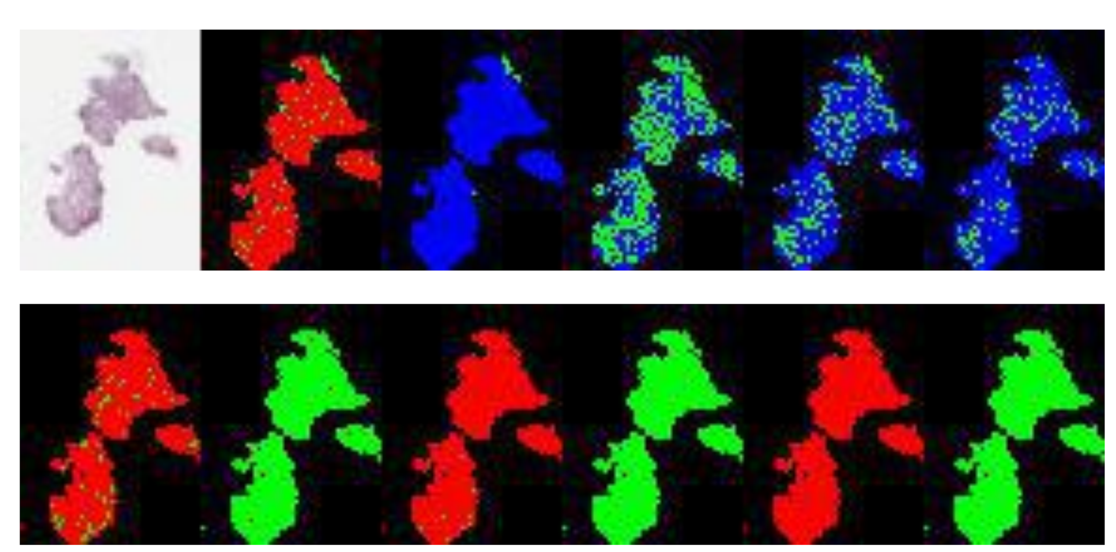
We adopt a simple feedforward neural network as the discriminative model D, which contains 3 *Dense-Relu-Dropout* blocks.

- **Thresholding Scheme:**

Given a patch X, if its image-level label is class K and correspondingly the other classes are R, then the thresholding scheme and its patch-level label updating would be performed by Formula

$$\text{Relabel } X \text{ as } \begin{cases} \text{Non-Dis} & \text{if } P(X,K) \leq S_K \\ & \text{and } P(X,R) \leq 0.5 \\ \text{Dis-to-}K & \text{else} \end{cases} \quad (1)$$

Results: (a) Contribution of Non-Dis Patches

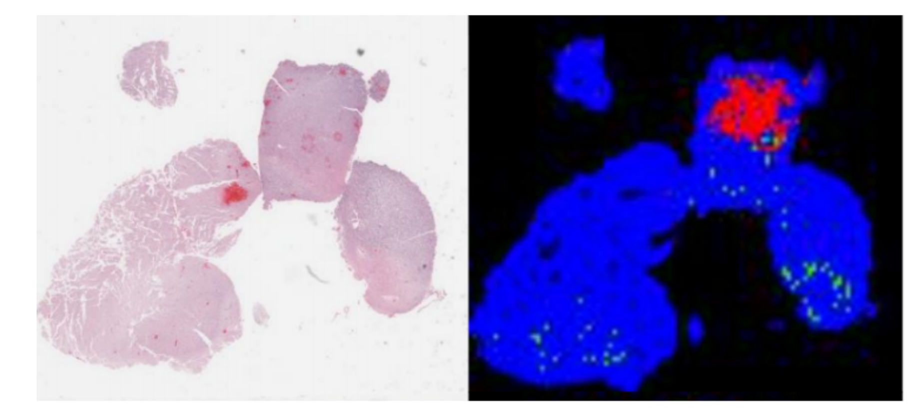


- Visualization scheme utilized for iterative labelling: **Blue** for **Non-Dis** patches, **red** for **Dis-to-*O*** (oligodendroglioma) patches and **green** for **Dis-to-*A*** (astrocytoma) patches.
- The recognization of Non-Dis patches can narrow down the set of possibly discriminative patches and the algorithm can therefore concentrate on the difference between the Dis-to-K patches. This benefit enhances the discriminative ability of the model and make it easier to reach the convergence.

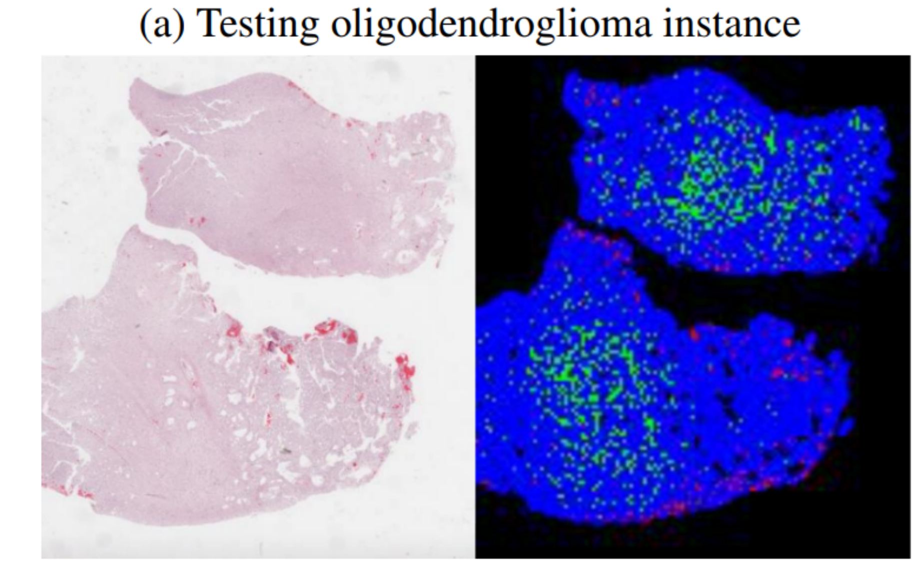
Results: (b) WSI Classification

Methods	Acc.
CNN-Feat-SVM	62.50%
Finetune-CNN-Feat-SVM	69.13%
Iter-Finetune-CNN-SVM[Discriminative]	76.62%
Iter-Finetune-CNN-SVM[Both]	**84.38%**

Results: (c) ROIs Visualization



(a) Testing oligodendroglioma instance



(b) Testing astrocytoma instance

Conclusions:

A. We proposed an iterative patch labelling algorithm to recognize Dis-to-K and Non-Dis patches, in order to address the WSI classification challenge with only image-level labels provided. Our method achieved the best classification performance of 84.38% on the MICCAI 2015 Challenge Dataset.

B. By identifying the discriminative patches, our model could produce a more explainable and reliable classification results, which are valuable to human pathologists in the diagnosis decision-making process.

C. Furthermore, our approach demonstrates **the importance of recognizing non-discriminative patches in image classification tasks.**