DEEP DICTIONARY LEARNING FOR COLORECTAL CANCER GRADING

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ABSTRACT

Cancer grading is one of the routine tasks done by pathologists and plays a key role in the treatment plan. In this paper, application of deep dictionary learning for automatic Colorectal Cancer (CRC) grading is investigated. Encouraging experimental results demonstrate the potential of the proposed pipeline.

1 INTRODUCTION

Colorectal Cancer (CRC) is the fourth most common cause of cancer related deaths, and accounts for approximately 10% of the cancer cases recorded worldwide (Stewart, 2016). Grading of CRC tissues is a routine part of the pathological analysis and plays a key role in the treatment plan. Also, about 70% of cancer deaths occur in low- and middle-income countries and AI has the potential to provide low-cost and reliable solutions. Although there is no accepted standard grading system, many cancers use the following: *Grade I* or low-grade that cancer cells resemble normal cells and usually grow more slowly, *Grade II* or moderate that look more abnormal and are slightly faster growing, and *Grade III* or high-grade look very different from normal cells and may grow more quickly. Example of tissues with different grades are shown in Figure 2. From computer vision and image processing perspectives, this can be treated as material and texture recognition problem.

Recently, a number of methods for automatic grading of CRC have been proposed in the literature (Awan et al., 2017; Zhou et al., 2019; Shaban et al., 2020). In order to incorporate the entire tissue micro-architecture for CRC grading purposes, Zhou et al. (Zhou et al., 2019) proposed cell-graph convolutional neural network (CGC-Net). It converts each large histology image into a graph, where each node is represented by a nucleus within the original image and cellular interactions are denoted as edges between these nodes according to node similarity. (Shaban et al., 2020) presented a context-aware deep neural network which is able to incorporate larger context than standard CNN based patch classifiers. It first encodes the local representation of a histology image into high dimensional features, then aggregates the features by considering their spatial organization to make a final prediction.

Recently, a deep dictionary learning approach has been proposed for texture recognition (Zhang et al., 2017). It is an end-to-end learning framework that the features, dictionaries, encoding representation and the classifier are all learned simultaneously (directly from the loss function). In this paper, application of deep dictionary learning using different CNN backbones is investigated for CRC grading.

2 METHODOLOGY

The network consists of an encoding layer integrated on top of convolutional layers, which ports the entire dictionary learning and encoding pipeline into a single model. It consists of dictionary, assignment, residuals, and aggregation layers (shown in the gray box in Figure 1). The residuals and assignment weights are calculated by pairwise difference between the input visual descriptors and the codewords of the dictionary. Finally, the residual vectors are aggregated with the assignment weights. More details can be found in (Zhang et al., 2017). Figure 1 shows the general block diagram of deep dictionary learning for CRC grading. Local image patches are extracted from the segmented tissue parts. Then, the network is applied on all the patches. The final CRC grading on a WSI is obtained by aggregation operators such as majority voting. It is an end-to-end learning framework, where the inherent visual vocabularies are learned directly from the loss function.

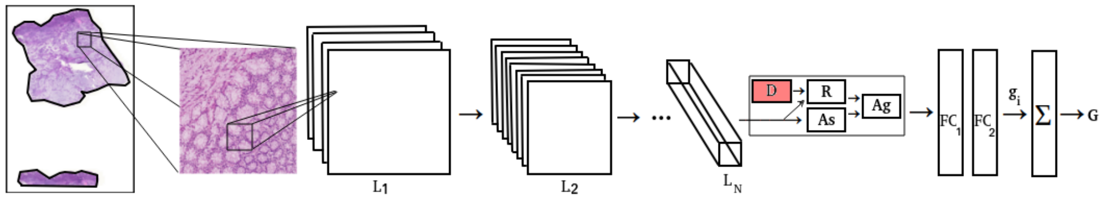

Figure 1: The general block diagram of deep dictionary learning for CRC grading; from raw WSI to tissue segmentation, local patches, patch-level labels, and image-level grading. L_i, D, R, As, Ag, FC are n-th layers, dictionary, residual, assignment, aggregation, and fully-connected, respectively. g_i, G, Σ are grading label for i-th patch, over-all grading for WSI, and the aggregation operator (e.g. majority voting).

Table 1: Patch- and image-level accuracies of deep dictionary learning using different CNN backbones.

Backbone	**ResNet18**	**ResNet50**	**VGG16**	**MobileNet**	**DenseNet**	**Inception**
Patch-level	92.2	92.0	90.6	90.9	91.8	92.4
Image-level	94.8	94.7	93.2	93.5	94.0	95.2

The features, dictionaries, encoding representation and the classifier are all learned simultaneously (gradient information passing to each component during back propagation, tuning each component).

3 Experimental Results

The dataset comprises of 36,750 non-overlapping images of size 4,548×7,548 pixels, extracted at magnification 20×. Each image is labelled as normal tissue, low grade tumour or high grade tumour by an expert pathologist. To obtain these images, digitised WSIs of 38 CRA tissue slides stained with H&E is used. All WSIs were taken from different patients and were scanned using the Omnyx VL120 scanner at 0.275 μm/pixel (40×). In total 139 images were extracted, comprising 71 normal, 33 low grade and 35 high grade cancer images. Samples of the dataset are shown in Figure 2. Table 1 reports the patch-level and image-level accuracies of deep dictionary learning using different popular backbone networks. The promising results demonstrate the potential of the proposed CRC grading pipeline.

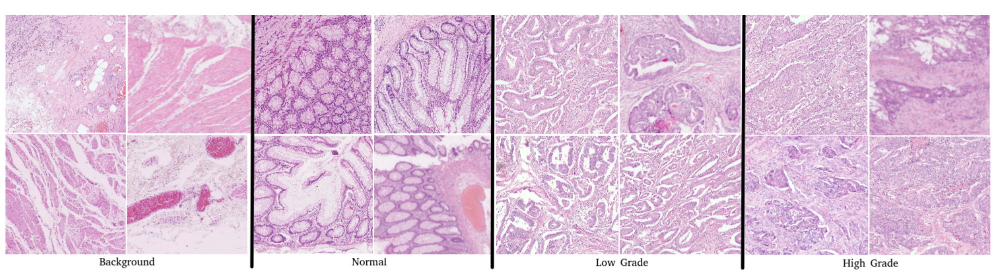

Figure 2: Samples from 4 classes of the Colorectal Cancer Grading Dataset.

References

Ruqayya Awan, Korsuk Sirinukunwattana, David Epstein, Samuel Jefferyes, Uvais Qidwai, Zia Aftab, Imaad Mujeeb, David Snead, and Nasir Rajpoot. Glandular morphometrics for objective grading of colorectal adenocarcinoma histology images. *Scientific reports*, 1(7):16852, 2017.

Muhammad Shaban, Ruqayya Awan, Muhammad Moazam Fraz, Ayesha Azam, David Snead, and Nasir M Rajpoot. Context-aware convolutional neural network for grading of colorectal cancer histology images. *IEEE Transactions on Medical Imaging*, 1:1, 2020.

Wild Christopher P. et al. Stewart, Bernard W. . In *World cancer report 2014*. WHO, 2016.

Hang Zhang, Jia Xue, and Kristin Dana. Deep ten: Texture encoding network. *CVPR*, 1:708–717, 2017.

Yanning Zhou, Simon Graham, Navid Alemi Koohbanani, Muhammad Shaban, Pheng-Ann Heng, and Nasir Rajpoot. Cgc-net: Cell graph convolutional network for grading of colorectal cancer histology images. *ICCV Workshops*, 1:1, 2019.