Multiple Instance Learning for Detection of Polyps in Computed Tomographic Colonography Images

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Abstract: Colorectal cancer(CRC) is a significant health problem in the world, the incidence of CRC can be largely preventable by early detection and removal of the polyps before they turn into the malignant structure. Most existing CAD system for polyps detection rely on fully supervised learning which requires the tedious manual annotation and precise colon segmentation. This paper proposed a method based on multiple instance learning and transfer learning. Our scheme firstly extracts many small patches from CTC images by using threshold segmentation method, then a pre-trained model was applied for feature extracting of instances, next pooling operator was used to aggregating these instance features into a bag, finally, classification result was obtained by a classifier. Our proposed method does not rely on accurate colon segmentation and the result show that it can achieve a high accuracy rate.

1 INTRODUCTION

According to the recent statistics from the American Cancer Society, both incidence and mortality of colorectal cancer(CRC) rank the third among all kinds of cancers in 2019 (DeSantis et al., 2019). The majority of CRCs are thought to arise from polyps, and the process can take 5-15 years for malignant transformation into cancer. Thus, the incidence of CRC can be largely preventable by early detection and removal of the polyps before they turn into the malignant structure. Nowadays, computed tomography colonoscopy(CTC) provides a non-invasive technique for colorectal cancer screening. However, it is a time-consuming task to review the result of the colonoscopy, furthermore, different radiologists often have different opinions, even for the same patient. To overcome the limitations, various computer-aided diagnosis (CAD) systems were developed for the detection of polyps in CTC images.

Generally speaking, the CAD systems consist of three main components: colon segmentation, feature extraction and classification. Polyp candidates on the colon surface are identified in colon segmentation step. Li et al. performed colon segmentation using a two-dimensional region growing algorithm on each CT slice image(Li et al., 2009). Chowdury and Whelan developed a method for colon segmentation using geometric features(Chowdhury and Whelan, 2011). Masutani et al. proposed a method to realize colon segmentation through thresholding of CT values and gradient magnitude values(Masutani et al., 2001). Subsequently, a centerline-based segmentation method was presented and improved the preformance(Frimmel et al., 2005). Moreover, a knowledge-based method was used for colon segmentation(Manjunath et al., 2015), and Wyatt et al. applied 3-D region growing technique to achieve the goal(Wyatt et al., 2000).

For feature extraction, the distinguishing features of polyps which are malignant are curvature, size, haustral folds, shape, colour and texture(Mittal et al., 2016). Hu et al. used Haralick's texture features for 3D space. They applied the Karhunen-Loeve(KL) transformation on these features to obtain new features and classified by the random forest algorithm. The volumetric curvedness and shape index is used for polyps detection based on colon segmentation (Zhu et al., 2009; Wang et al., 2008). Besides, Xu and Zhao developed an algorithm based on complementary geodesic distance transformation in consideration of challenges for polyps detection due to haustral folds(Xu and Zhao, 2014). The morphological

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features, statistical and textural features of polyps in CT images are extracted and classified by the different classification algorithm.

Most existing CAD systems comprise of three stages: identify polyps candidates in images; extract features for each candidate; classify each candidate as negative or positive. These approaches rely on fully supervised learning, which requires the tedious manual annotation of object location in a training set. Moreover, there does not exist any public CT colonography dataset with annotated polyps.

Because of polyps are too small relative to the image's size, and many noises in CT images, classify for the whole images do not perform well. To overcome the limitations, we proposed a MILTL method based on multiple instance learning(MIL) and transfer learning for CT images.

In remainder of this paper is organized as follows. We describe our method in section II and report the experiments and results in section III.Section IV provides the discussions and conclusions.P

2 METHOD

In this section, we will firstly introduce the formulation of MIL, then define transfer learning, finally show the structure of our proposed system.

2.1 Multiple Instance Learning

Here we review the definition of MIL Formally, the task is to learn $f : X \longmapsto Y$ from a training data set $D = \{(x_1, y_1), ..., (x_m, y_m)\}$, where $X_i = \{x_i 1, ..., x_i m\} \subseteq X$ is called a bag, $x_{ij} \in X\,(j \in \{1, ..., m_i\})$ is an instance, m_i is the number of instances in X_i, and $y_i \in Y = \{Y, N\}$. X_i is a positive bag, i.e. $y_i = Y$, if there exists x_{ip} that is positive, while $p \in \{1, ..., m_i\}$ is unknown.The goal is to predict labels for unseen bags (Zhou, 2017).

2.2 Transfer Learning

In recent years, deep convolutional neural networks(DCNN) have rapidly become a methodology of choice for analyzing medical images. However, robust supervised training of a DCNN by making use of a large amount of annotated training images(LeCun et al., 2015). Transfer learning is essentially the use of pre-trained networks to try to work around the requirement of large data sets for deep network training(Litjens et al., 2017). Two transfer learning strategies were used for medical images classification, the first is using a pre-trained network as a feature extractor and the second is fine-tuning a pre-trained network on training data.

2.3 Proposed System

The overall structure of the training of our proposed system is shown in Figure.1 Firstly, the colon lumen is segmented from the CT images. Secondly, many small patches are extracted from an image. In our task, an image is natural to regard as a bag and patches which are extracted from the image as its instances. After that, we used the pre-trained network to learn these instance features, then a pooling layer to aggregate these instance scores into bag score. Finally, we initialize the classification layer with random weights and configure it for CT images classification.

2.3.1 Colon Segmentation

First, threshold segmentation has been used for the detection of colon lumen, then the morphological operation is applied for noise elimination.

2.3.2 Instance Identified

The CT images are divided into several parts based on the result of colon segmentation. This image is viewed as a bag, and each part is treated as an instance in the bag. The colon segmentation and instance identified can be seen in the Figure2.

2.3.3 Feature Extraction

In feature extraction, we use a VGG-Net trained on the ImageNet dataset as a fixed feature extractor. We first extract the features of instance through the feature extractor, then a pooling layer is used to aggregate these instance features into a bag. We look at three pooling method(max pooling, mean pooling and log pooling) in our proposed system.

2.3.4 Classification

When we performed the classification step, we build a classifier from three fully connected layers which use the cross-entropy to calculate the cost.

3 EXPERIMENTS AND RESULTS

3.1 Materials

The CTC data used in this study include 67 cases from The Cancer Imaging Archive(TCIA), which consisted

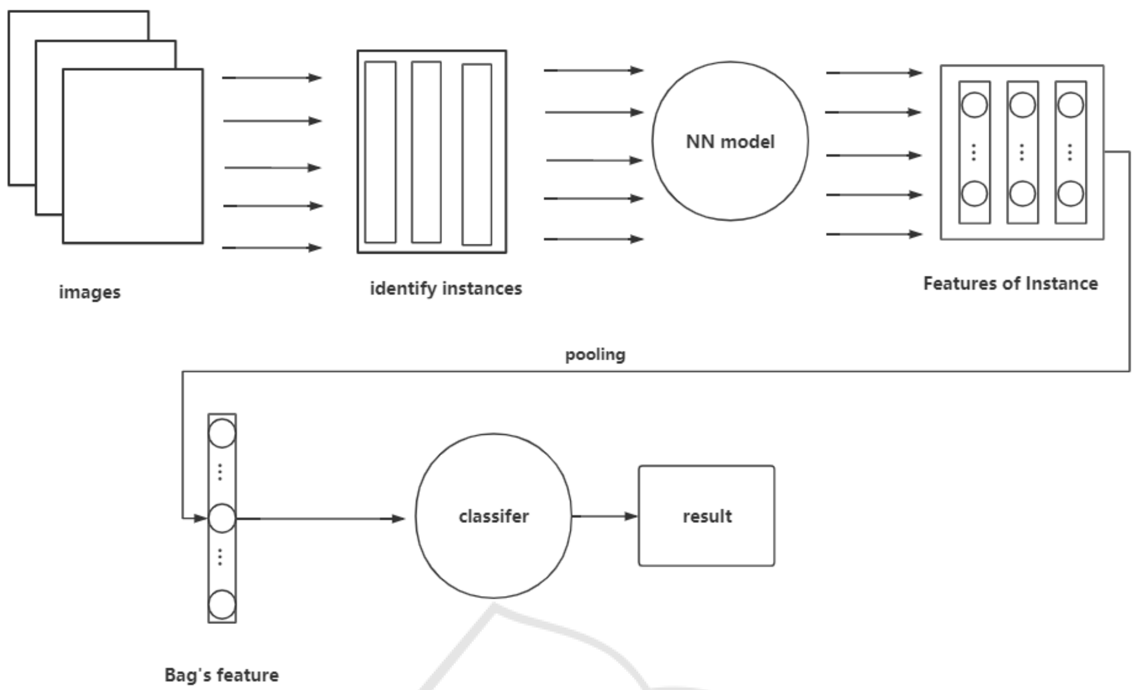

Figure 1: Proposed System.

of 39 cases with 6-9 mm polyps and 28 cases which have at least one 10 mm or larger size polyp was found. Because each patient case includes two scans, supine and prone, there are in total 180 positive images (with polyp). And we random sampled 180 negative images from the case with no polyp found.

The TCIA CTC datasets were acquired by using at least a 16 slice CT scanner with 0.5-1.0 mm collimation, 0.98-1.5 pitch, 0.8 mm reconstruction interval, 1-1.25 mm slice thickness, 50 effective mAs, 120 kVp, CT slice size of 512*512 pixels(Ren et al., 2018).

3.2 Experimental Setting and Evaluation

In this part, we make two comparison experiment by using pre-trained VGG-16 and ResNet50, respectively. The VGG-16 and ResNet50 are available for use in the TensorFlow models repository. In the evaluation of classification performance, a ten-fold cross-validation method was used to minimize the evaluation bias. The accuracy, recall, precision and AUC are evaluation metrics in our study. Also, the evaluation is conducted with 10 trails running for statistical results.

Table 1: Comparisions of Algorithms.

methods	accuracy	recall	precision	AUC
VGG	0.7778	0.8056	0.7838	0.7778
ResNet	0.8333	0.8611	0.7750	0.8333
max-MILTL	**0.9028**	**0.9167**	**0.8250**	**0.9167**
mean-MILIL	0.8472	**0.9167**	0.8049	0.8333
log-MILIL	0.8750	0.8889	0.8049	0.8858

3.3 Result

It can be seen from Table I that the models we constructed are better than the existing pre-trained VGG-16 and ResNet-50. Moreover, compared with the other two, MILTL with max-pooling layer was the best with the accuracy of 0.9028 and AUC of 0.9167.

4 CONCLUSION

The framework provided by MIL is particularly suitable for CTC image classification. In this paper, we proposed a new method for the automatic detection of colon polyps based on CTC images. This method includes colon segmentation, instance identified, feature extraction and classification. Due to the nature of MIL method, the colon segmentation does not require precise segmentation results, which undoubtedly provides convenience and saves time for the polyps detection. According to our experiments, the proposed

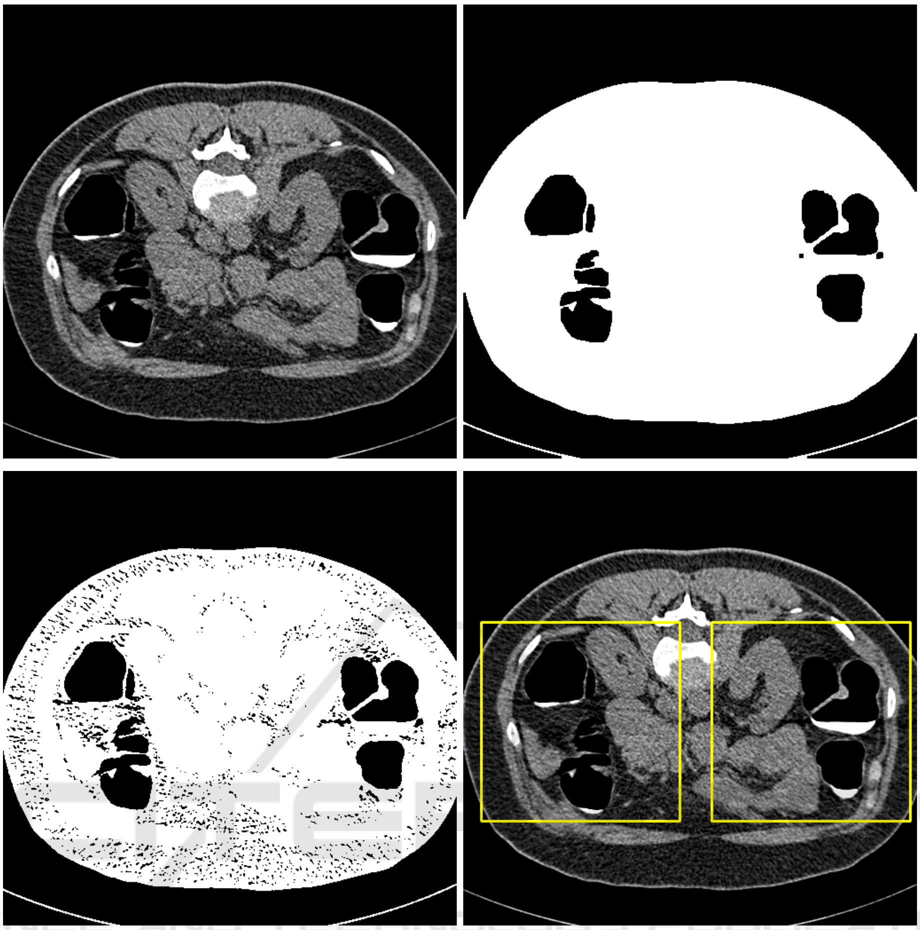

Figure 2: Colon Segmentation and Instance Identified.

method can improve the accuracy of classification. In the future, we will focus on the probability relation between bag and instances, to make sure the label for instances, especially for positive instances.

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