Learning-based cell detection in digital pathology

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Abstract: In blood testing, knowing the ratio and throughput of blood cells is crucial to help doctors make a clinical diagnosis. Here we propose a deep transfer learning strategy for accurate cell detection for digital pathology.

1. Introduction

Digital pathology is a critical technique to digitally produce high-resolution images of histological slides of microscopic specimens. Due to the growing availability of digital detectors and automation, it has become increasingly common and important. These digitized whole slide images afford the possibility of applying post image processing for applications of category classification, target detection, and segmentation for clinical diagnosis [1].

In this paper, to improve the performance and inference speed of target localization and recognition, with the help of advanced deep learning method, we propose a transfer learning strategy for blood cell detection. By training a detection model with natural images and by reusing pre-trained weights, knowledge learned from one domain can be effectively transfered to a new domain and training time is significantly reduced.

2. Principle and Method

In object detection, not only multiple objects in a single image need to be correctly recognized (recognition), but also their individual locations are required to be detected (localization). For a specific task, substantial image data has to be collected and annotated for detecting targets. However, for professional communities like disease diagnosis, building a large-scale and high-quality annotated dataset becomes challenging, complex and sometimes expensive. Besides, updating all the weights during training is extremely time-consuming.

Transfer learning is a technique aiming at transferring the knowledge from the source domain to the target domain by relaxing the hypothesis that the training data must be independent and identically distributed with the test data [2]. Lower-level representations like edges and curves can be transferred to a new task, and only the higher-level features need to be learned from the new data, even the amount of data is not huge [3, 4]. This will lead to a great positive effect that the deep model in the target domain is not necessary to get trained from scratch, thereby significantly reducing the demand of training data and training time. Such advantages motivate us to against problems of insufficient training data and tremendous training time by initializing the target deep model with parameters transferred from a pre-trained model.

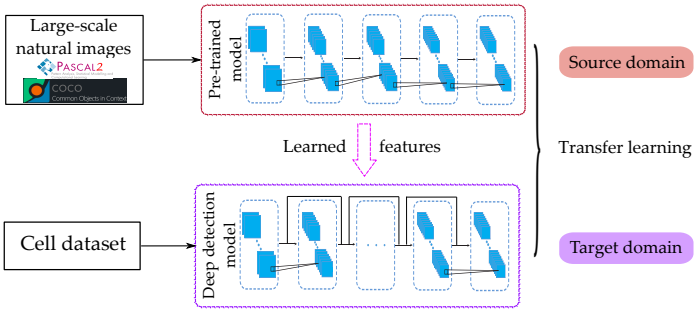

Fig. 1. Principle of transfer learning for cell detection.

Considering the principle of transfer learning and characteristics of the data, pre-training the deep detection network, YOLOv3 [5], is achieved using large datasets of natural images. The cell detection model is composed of three modules, *Darknet-53*, *Multi-scale* and *Detection*. The training scheme contains three stages:

1. Train parameters in the *Darknet-53* module by freezing the other two modules with the MS COCO dataset;
2. Train parameters in the *Multi-scale* module with the Pascal VOC dataset;
3. Train parameters in the *Multi-scale* module again and the *Detection* module with blood cell data.

By doing so, the model parameters and hyper-parameters can be learned and then transferred to the target domain. Low-level weights are directly obtained from the pre-trained model, and high-level kernels are further fine-tuned for the respective detection tasks. In this way, transfer learning gives the target model a reasonable initialization and reduces the number of parameters that need to be updated, as well as ameliorates the burden of training a large and deep detection model from scratch.

3. Results

We use the small-scale Blood Cell Count and Detection dataset for blood cells detection[1]. Totally, the dataset contains 364 images and the respective annotations. Annotations are labeled by manually outlining the individual cells. There are three kinds of cells, red blood cell (RBC), white blood cell (WBC) and platelet. Comparatively, the RBC and WBC are larger and the platelet is smaller, meaning that recognizing the platelet is more challenging. In some cases, two or more RBCs are so close and clustering that they even have overlapping regions. On the other hand, although RBCs are mostly homogeneous in shape and size, they still vary greatly in morphology and images often contain visible debris. Therefore, we consider these variables more challenging factors and may pose problems for automated detection methods.

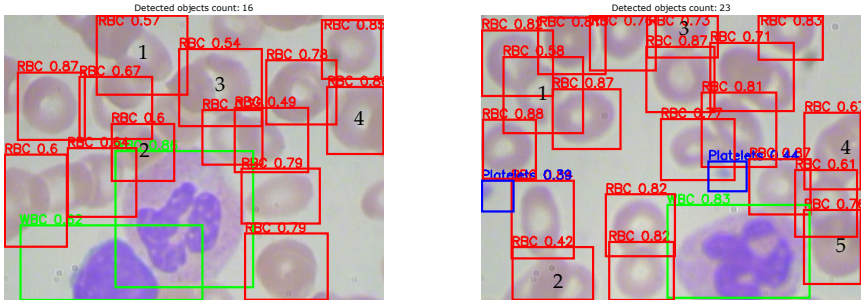

Fig. 2. Blood cell detection results.

In Fig. 2, we show detection and counting results of the individual cell types with their bounding boxes. On the top of each bounding box, prediction score of each target is also given. We can see that, even with overlapping regions, most RBCs (in red) can be correctly located and recognized. Some RBCs that are not annotated in the annotation files and labeled with numbers in Fig. 2 can be surprisingly found out. As for WBC cells (in green), since there is only one or two WBCs in a single image and its size is relatively large, more information and features can be extracted by the network. That's why in Fig. 2, all WBCs can be detected with pretty high scores. For platelets (in blue), in some cases they are out-of-focus and blurred, posing difficulty due to unclear edges and main structures in detection. However, despite scores are not very high, the trained network can still detect them. As for the training time, with the help of transfer learning, the time consumption in training is greatly reduced from 6.8 h to 2.5 h, saving tremendous time in building a blood cell detection model.

4. Conclusion

In this paper, we propose a deep transfer learning method for blood cell detection in digital pathology. By transferring weights pre-trained with natural images, time-consuming network training from scratch is thus avoided and superior detection is achieved even with insufficient data.

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[1] see https://github.com/Shenggan/BCCD_Dataset