Parasite Detection in Thick Blood Smears Based on Customized Faster-RCNN on Smartphones

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***Abstract*— Malaria is a worldwide life-threatening disease. The gold standard for malaria diagnosis is microscopy examination, which includes thick blood smears to detect the presence of parasites and thin blood smears to differentiate the development stages of parasites. Microscopy examination is of low cost but is time consuming and error-prone. Therefore, the development of an automated parasite detection system for malaria diagnosis in thick blood smears is an important research goal, especially in resource-limited areas. In this paper, based on a customized Faster-RCNN model, we develop a machine-learning system that can automatically detect parasites in thick blood smear images on smartphones. To make Faster-RCNN more efficient for small object detection, we split an input image of 4032×3024×3 pixels into small blocks of 252×189×3 pixels, and then train the Faster-RCNN model with the small blocks and corresponding parasite annotations. Moreover, we customize the convolutional layers of Faster-RCNN with four convolutional layers and two maxpooling layers to extract features according to the input image size and characteristics. We perform experiments on 2967 thick blood smear images from 200 patients, including 1819 images from 150 patients who are infected with parasites. The customized Faster-RCNN model is first trained on small image blocks from 120 patients, including 90 infected patients and 30 normal patients, and then tested on the remaining 80 patients. For testing, we also split each input image into small blocks of 252×189×3 pixels that are screened by our trained Faster-RCNN model to detect parasite coordinates, which are then re-projected into the original image space. Detection rates of our system on image level and patient level are 96.84% and 96.81%, respectively.**

Keywords—Faster RCNN, deep learning, malaria, computer-aided diagnosis

I. INTRODUCTION

Malaria is a worldwide life-threatening disease. According to the World Health Organization malaria report in 2018, about 219 million malaria cases were detected worldwide in 2017, causing approximately 435,000 deaths [1]. Microscopy examination continues to be considered as the gold standard for malaria diagnosis [2]. It includes two types of blood smears: thick blood smears and thin blood smears. Thick blood smears contain more blood and are used to detect the presence of malaria parasites, whereas thin blood smears allow differentiating parasite species and development stages. Microscopy examination is low-cost and is widely available. However, it is time-consuming and the effectiveness of microscopy diagnosis depends on the parasitologists' expertise [3]. In situations with poor quality control, inaccurate results can lead to misdiagnosis or inappropriate treatment [4]. Therefore, the development of a rapid and automated parasite detection system for malaria diagnosis in thick blood smears is an important research goal, especially in resource-limited areas.

In recent years, the development of small camera-equipped devices, such as smartphones, has offered a new way for malaria diagnosis in resource-poor regions [4, 5]. Table I is a summary of the existing smartphone-based parasite detection approaches in both thin and thick blood smears. References [6]-[13] focused on the design and development of mobile devices for capturing images to replace current microscopes, while references [14]-[18] combines both image capture and image processing in a practical system or a software application. So far, most of the work has concentrated on thin blood smears, and only the system in [16] has been developed for parasite detection in thick blood smears.

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TABLE I. MOBILE DEVICES FOR MALARIA DIAGNOSIS

Authors	Objective	Experimental Results	Thin or thick blood smears	Remarks
Breslauer et al., 2009. [6]	Build an mobile phone microscope to image P. falciparum-infected and sickle red blood cells in brightfield	Illumination variation, image distortion and pixel non-linearity for mobile phone miscrospcopy are minimized.	thin / thick	Focus on the design and development of mobile devices for capturing images
Tuijn et al., 2011 [7]	Capture microscopy images with different resolutions using a variety of mobile phones	Clear images are captured using mobile phone cameras of 2 megapixels (MP) up to 5MP	thin	
Kaewkamnerd et al., 2012 [11]	Develop an image acquisition module and an image analysis module	- 40 infected films and 20 normal films - Accuracy of 95% for parasite detection and 68.5% for background detection	thick	
Skandarajah et al., 2014 [8]	Customize microscope compatible with mobile phones from multiple manufacturers	-	thin	
Quinn et al., 2014 [12]	Capture images with mobile devices and process images with machine learning techniques on a server for remote diagnosis	- 133 patients with 2903 images - 20% recall and 90% predictive rate	thick	
Pirnstill et al., 2015. [9]	Support image capture to distinguish hemozoin from background and artifacts	Qualitative results	thin / thick	
Coulibaly et al., 2016 [10]	Evaluate performance of portable microscope and mobile phone attachment to a conventional light microscope	- 223 patients - Sensitivity and specificity of the handheld microscope are 80.2% and 100.0% respectively	thick	
Quinn et al., 2016 [13]	Process images using deep learning techniques on a server for remote diagnosis	- 1182images - 97% predictive rate	thick	
Cesario et al. 2012 [14]	Develop a mobile system for vector borne disease diagnosis	Qualitative results	thin	Implement both image capture and image analysis on mobile devices
Dallet et al., 2014 [15]	Develop an Android application based on annular ring ratio method for mobile devices	- Takes less than 60 seconds to give a diagnosis - Useful only for circular shapes	thin	
Rosado et al., 2016 [16]	Develop a mobile system based on machine learning techniques for parasite detection	- 6 patients with 94 images - 92% detection rate	thick	
Rosado et al., 2017 [17]	Develop a module based on machine learning techniques for species classification	- 566 images - 73.9% to 96.2% sensitivity and 92.6% to 99.3% specificity	thin	
Eysenbach et al., 2017 [18]	Develop an application based on cascaded classifiers	- 555 positive and 777 negative slides - Average accuracy of 91% and AUC value of 66%	thin	

The objective of this paper is to develop an automated malaria screening system for parasite detection in thick blood smears on smartphones. For our task of detecting parasites in thick blood smears, we choose to use a customized Faster-RCNN model [19] because of its outstanding performance for object detection. Compared to the work in [16], we apply deep learning for parasite detection and achieve more accurate results on more patients, including both normal and abnormal patients. The paper structure will be as follows: Section 2 describes our customized Faster-RCNN model; Section 3 describes the data we used for our experiments; Section 4 shows the experimental results for 200 patients; and Section 5 concludes the paper with the discussion and conclusion.

II. CUSTOMIZED FASTER-RCNN MODEL

After the great success of CNN [20] in classification, region-based CNN (RCNN) models such as RCNN [21] and fast-RCNN [22] have achieved remarkable results in object detection. Faster RCNN [19] is currently one of the most popular object detection models since it solves the computational burden of RCNN-based methods and makes real-time detection possible. Faster-RCNN is a combination of Regional Proposal Network [19] and fast-RCNN.

We develop a rapid and robust system for automated malaria diagnosis on smartphones in thick blood smears using a customized Faster-RCNN model. To improve the detection performance of Faster-RCNN for small objects, we first split images of 4032×3024×3 pixels into regions of 252×189×3 pixels, and then train a customized Faster-RCNN model with these regions and corresponding manual ground-truth annotations. The customized Faster-RCNN model includes four convolutional layers and two max-pooling layers. For testing, we also split blood smear images into regions of 252×189×3 pixels, which are screened for parasites using our cascaded Faster-RCNN model. The detected parasite coordinates are then re-projected into the original image space for visualization and evaluation. We illustrate the flowchart of our customized Faster-RCNN model in Fig. 1.

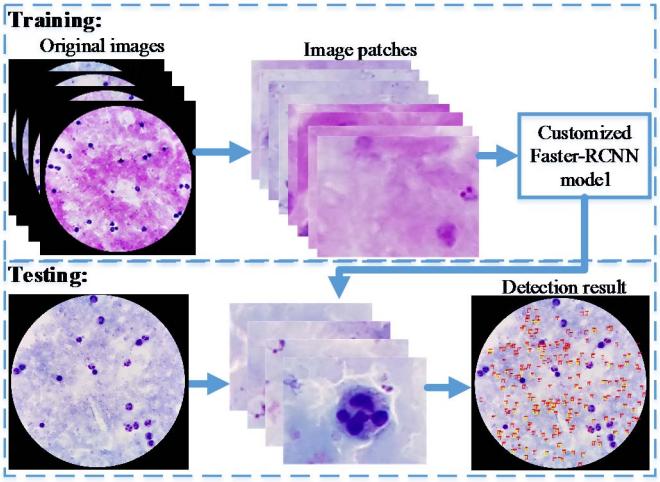


Fig. 1 Flowchart of our automated malaria screening system.

III. Data Acquisition and Data Partitioning

A. Data Acquisition

We photographed Giemsa-stained thick blood smear slides from 150 *P. falciparum* infected patients and 50 normal patients at Chittagong Medical College Hospital, Bangladesh, using a smartphone camera attached to the eyepiece of a microscope. We captured 2967 images with 100x magnification in RGB color space, with a 3024×4032 pixel resolution. An expert blood smear reader manually annotated each image at the Mahidol-Oxford Tropical Medicine Research Unit (MORU), Bangkok, Thailand. We de-identified all images and their annotations, and archived them at the National Library of Medicine (IRB#12972).

B. Data Partioning

We split the dataset into five folds on patient-level. Each fold includes 30 infected patients and 10 normal patients. The system performance is evaluated with five-fold cross valuation. For each run, the customized Faster-RCNN model is first trained on small image blocks from 120 patients, including 90 infected patients and 30 normal patients, and then tested on the remaining 80 patients. For testing, we also split each input image into small blocks of 252x189x3 pixels that are screened by our trained Faster-RCNN model to detect parasite coordinates, which are then re-projected into the original image space.

IV. Experimental Resutls

A. Evaluation Metric

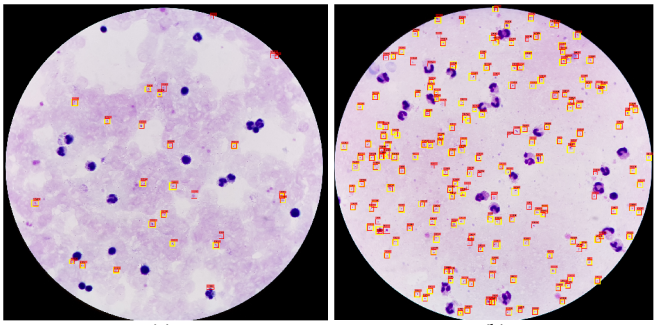
To evaluate the system performance, we calculate the detection rate R_{det}, which is the ratio of the detected true parasite numbers and the total number of parasites in the annotated ground truth:

$$R_{det} = \frac{N_{true}}{N_{total}}. \qquad (1)$$

N_{true} is the number of detected parasites that overlap the ground truth, and N_{total} is the total number of parasites in the ground truth. When N_{true} and N_{total} are computed for an image, R_{det} designates the detection rate on image level; when N_{true} and N_{total} are computed for a set of patient images, R_{det} designates the detection rate on patient level.

B. Results

Figure 2 shows two examples of detected parasites based on our customized Faster-RCNN model. The detection rates of our system on image level and patient level are 96.84% and 96.81%, respectively (Fig. 3).



(a) (b)

Fig.2 Examples of parasite detection based on a customized Faster-RCNN. (a) Thick smear image with sparse parasites. (b) Thick smear image with dense parasites.

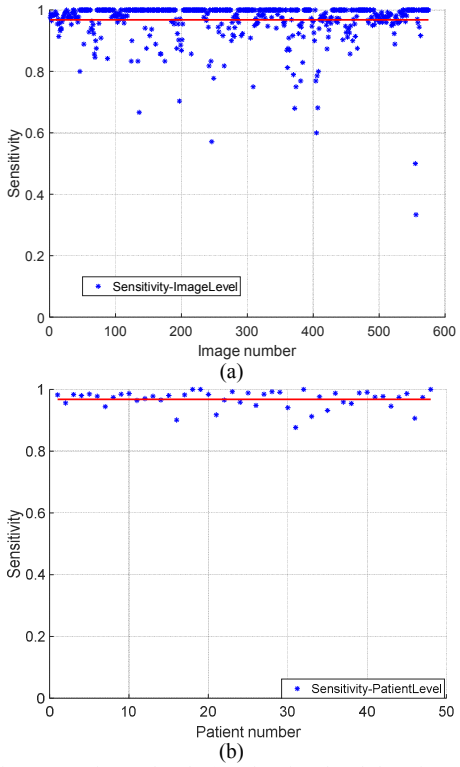


Fig.3 Detection rate on image level (a) and patient level (b) using a customized Faster-RCNN model.

V. Conclusion and Discussion

In this paper, we have developed a rapid and automated screening system for malaria parasites in thick blood smears on smartphones based on a customized Faster-RCNN model. This model can be easily imported into a smartphone and detects parasites without the need for experienced microscopists. Our future work will focus on reducing false positives.

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