Learning from the Scratch for Tuberculosis (TB) Bacilli Detection Using DSOD

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ABSTRACT
Tuberculosis (TB) is an infectious disease caused by the micro-bacteria Tuberculosis which can be transmitted through sputum sprinkling. Tuberculosis is a direct infectious disease caused by tuberculosis bacilli. Most tuberculosis bacilli attack the lungs but It could also be other organs of the body. Several studies that have been conducted previously aimed to reduce the burden of observing Tuberculosis bacilli using the processing method digital image. As technology continues to develop, the methods used to process digital images are also increasing. In this study, researchers used Deep Learning in digital image processing. This method aims to make the system or machine able to recognize tuberculosis bacilli with various kinds of data that have been shown. Deep Learning Method trains the machine to recognize Tuberculosis bacilli through learning various images of bacilli under varying conditions so that the machine can recognize the tray under various conditions slides. We believe that a fast and reliable diagnostic aid system with accurate information to help medical workers in the field is necessary.

Keywords: *Tuberculosis, object detection, Convolutional Neural Network.*

1. INTRODUCTION

Tuberculosis (TB) is one of the top 3 contagious diseases that cause death worldwide [1]. TB is caused by bacilli Mycobacterium tuberculosis. Although it is a curable disease, the death rate of TB is up to 13.57% in 2018 [2]. Moreover, one-third of the estimated incident cases (3 million) remain unknown to the health system due to an underreporting of detected cases and underdiagnosis [2]. Most of the underreporting and underdiagnosis cases happened in India (25%), Nigeria (12%), Indonesia (10%), and the Philippines (8%) [2]. Therefore, improvements in the accessibility of TB diagnosis and treatment are urgently required in these countries.

There are several established methods to diagnose TB i.e., microscopic analysis, polymerase chain reaction (PCR), electronic nose system, etc. [3]. Among other methods, sputum smear microscopy is the most used method, especially in developing countries, because it is simple, low cost, and easy to maintenance [4] [5]. Prepared and stained sputum specimen is analyzed manually under a microscope. TB bacilli is a Gram-positive bacillus, on a Gram-stained smears specimen of a patient with TB, bacilli can be detected [6]. TB bacilli counted manually depending on technician observation. Generally, a laboratory technician needs about 40 min – 3 h to examine 100 fields of view on each prepared specimen [6] [7]. The number of detected TB bacilli used to determine the diagnosis [3]. A prompt and precise diagnosis method of TB is essential to control the individual treatment and prevent further contagion [8]. The manual microscopic method is strenuous and time-consuming, gives various sensitivity and high false-negative rate detection [9] [10] [11].

Much research regarding TB bacilli detection has been reported. Rulaningtyas, et al. [12] developed an automatic classification of TB bacilli using a neural network. First, feature extraction was conducted to find the morphology (shape) of TB bacilli. The features were arranged into a vector and submitted to the neural network. Then, bacilli were classified by the backpropagation method. Although this research showed good TB bacilli classification results, this method used handcrafted feature vectors to discriminate bacilli pixels from non-bacilli pixels based on the morphology shape. Therefore, the performance heavily depends on bacilli features [13]. Khutlang, et al [5] proposed an automatic detection of TB

bacilli based on two one-class classifiers. The first stage classification was done used a one-class pixel classifier. The object output was filtered based on the object area. Features (Fourier, moment, eccentricity) were extracted from the remaining objects. Then, the second one-class object classification was done in different feature sets. The mixture of Gaussians performed the best result in first stage classification, but the accuracy of object outline detection is low, resulting in a low percentage of correctly classified pixels (75.74%). Ghosh, et al. [14] proposed an automatic TB diagnosis by hybrid (crisp and fuzzy data representation) approach. Sputum image was pre-processed before segmented using a gradient-based region growing technique to find the accurate contour of TB bacilli. Then, the features (shape, color, and granularity) of TB bacilli were extracted to generate individual fuzzy classification. Finally, the individual classification was combined to strengthen the diagnosis. The result showed quite high sensitivity (93.9%) and specificity (88.2%). Unfortunately, overlapped bacilli were failed to identify.

CNNs is the most popular DL-based method for its remarkable improvement in prediction performance using big data and plentiful computing resources [15]. Automatic detection of TB bacilli by CNNs successfully identified both single and touching bacilli [13]. Most of the recently advanced object detection lies on fine-tuned of pre-trained CNNs in ImageNet [16]. This process can generate the final model quickly and requires way fewer instance-level annotated training data than the classification task [17]. Yet, several limitations are undeniable, i.e., limited design space on network structures, learning optimization bias, and domain mismatch [17]. These problems can be overcome by a Deeply Supervised Object Detector (DSOD) framework. DSOD framework can learn object detectors from scratch [18]. As the author's knowledge, there is no research about TB bacilli detection based on the DSOD framework reported. These facts show a great research opportunity. Therefore, in this work, we proposed an enhanced architecture of the DSOD framework for TB Bacilli detection based on the Deep Learning model.

2. DSOD ARCHITECTURE

We applied CNN-based DSOD architecture for TB Bacilli detection implementation. DSOD architecture is a Deep Learning method for object detection based on the proposal region-free structure. This approach allows training to converge without using the pre-training model for initiation. The backpropagation during training steps requires the adjusted weight to flow from the rear side to the front side of the model. This flow must suit well in the parameters after and before the ROI pooling layer in case of the detection task. Therefore, DSOD derived their work from the SSD framework for their base to solve the proposal-free model's structure for learning from scratch.

Figure 1 shows DSOD model architecture in detail. As can be seen here, their plain network is closely related to SSD.

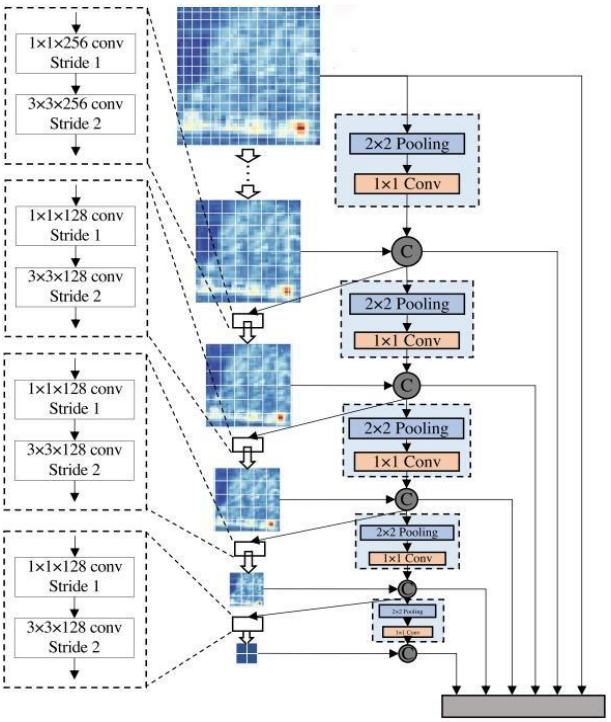

Figure 1 DSOD Architecture proposed in [18], their works are based on proposal-free and multi-scale network.

3. EXPERIMENTAL SETUP

Before designing a TB bacilli detection system, it is necessary to set a sputum smear image data. These data were used for training the Deep Learning model. We used the dataset as presented in [19]. The data consist of the actual image taken from the patient's sputum smear slides. Sputum slides were part of the smear examination routine by laboratories expert in a medical facility. One of the critical components for slides preparation was the smearing process. It contributes to sputum smear evenness coloring quality. One example smearing process that causing the sample's quality degradation was during the patient's sputum spread appears only on the first 1/3 slide middle. This happened due to pressure intensity change applied to the applicator during slides preparation. Another example is the quality of the dye. Therefore, the images in TBDB [19] dataset consist of sputum smears that are normal and excessive stains. We further followed the ground truth and label class naming for each type of sample in their dataset.

4. RESULT AND ANALYSIS

In this section, the experiment result is elaborated. We adopted the sputum smear images prepared in TBDB [19] with additional images taken from [20]. We selected images that have high similarity in hue, contrast

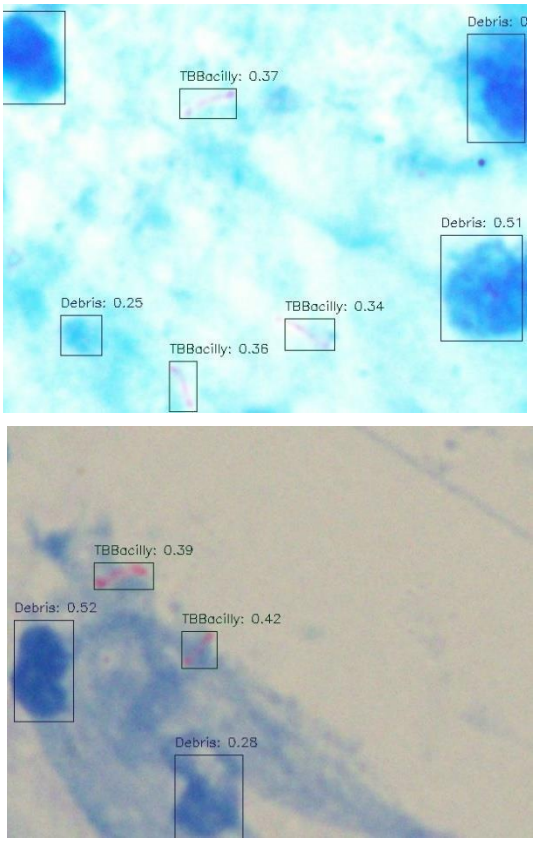

Figure 2 The Tuberculosis bacilli detection result among sputum smear images dataset combination.

and intensity with the previous dataset. A total of 600 images were prepared for our dataset. We split the dataset into 90 images for the testing phase and 510 images for the training and validation phase. We used different label arrangements compared to TBDB. We also used 2 labels which are TBBacilli and debris. We combined non-TB Bacilli and stain residues into 1 new category which we called debris.

We performed our experiment using the Caffe platform. Further detail for the hyperparameter variables that we used was 1. learning rate is set into 0.01, 2. Max Iteration is set into 15360, 3. Learning policy is set into multistep. 4. Step-value were set into 2560, 5120, 7680, 10240, and 12800. Using GTX1080Ti VGA card, we were able to finish the whole training session in 2 hours. We purposedly deployed a high value of learning rate and at the end of the iteration, the learning rate dropped to 0.0003125. High-value learning rate deployment was intended for making the training process faster and gaining coherent weight in a short time for training from the scratch.

We observed DSOD performance during the training, validation, and testing phase. Despite image number limitation and the model's weight had no previous knowledge at all regarding medicinal images and cell in general. The model delivered good learning ability during its early iteration. The situation continued all along with the iterations. There was no observable high error fluctuation.

Our experiment was assessed using mAP metric for each category. The TBBacilli detection gave prediction accuracy AP 72.32% while detection prediction was 70.88%. The inference was straight forward, we used 1000 images from unlabelled data. Figure 2 shows our detection result using DSOD model weight. DSOD performed quite well, despite hue and background intensity variation. It can locate TB bacilli among noise or colour variation in the background.

5. CONCLUSION

Our experiment results show that DSOD model performed well despite its challenges. Image data that corresponds to the medical world is always limited in number. Medical images observation especially sputum smear images that contain TB bacilli could have benefit from recent advances in Deep Learning. However, further comparisons toward other Deep Learning model is needed for verification.

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