Performance Evaluation of Binary Classification of Tuberculosis through Unsharp Masking and Deep Learning Technique

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Abstract— **The latest World Health Organization (WHO) study in 2018 shows that about 1.5 million people died and around 10 million people are infected with tuberculosis (TBC) each year. Moreover, more than 4,000 people die every day from TBC. Important work can be found in automating the diagnosis by applying techniques of deep learning (DL) to the medical image. DL requires a large number of high-quality training samples to reach better performance. Due to the low contrast of TBC x-ray images, the image obtained is poor in quality. Our work assesses the effect of image enhancement on the performance of the DL technique based on this problem. An image enhancement algorithm will highlight the overall or local characteristics of the images, and highlight some interesting features. Specifically, an image enhancement algorithm called Unsharp Masking (UM), is evaluated. The enhanced image samples are then fed to the pre-trained ResNet model for transfer learning. In a TB image dataset, we achieve 88.69% and 96.15% of classification accuracy and AUC scores, respectively. All the results are obtained using the Shenzhen dataset which is available in the public domain.**

Keywords: Tuberculosis detection, Deep Learning, Image Enhancement, Binary Classification.

I. Introduction

Millions of people around the world die each year because of TBC. Around 1.5 million deaths due to TBC are reported in 2018 alone, according to WHO report. It is mainly prevalent in Southeast Asia and Africa. This is a highly infectious disease caused by a tuberculosis of the bacillus mycobacterium. It is reported that the cheapest and most popular diagnostic techniques such as sputum smear microscopy have sensitivity problems [1]. In recent years, DL has performed well in the area of image recognition and classification, and the most popular models are deep learning based convolutional neural network (CNN) model. Deep learning techniques have been successfully used in several disciplines, such as surveillance system [2], face recognition [3] [4], autonomous cars [5], vehicle classification [6], and many others [7] [8] [9]. In addition, there are already numerous CAD (computer-aided design) systems that use CNNs to diagnose disease [10] [11], but their application to TBC detection remains limited. In recent literature, some automated TBC detection systems have utilized the DL technique, such as the works proposed by Lopes and Valiati [12], Lakhani and Sundaram [13], Liu, et al. [14], and Hwang et al. [15]. It is noteworthy that different from the aforementioned initial works, our research focuses on evaluating the effect of the pre-processing step for the performance of the DL technique thoroughly.

It is common that regardless of the training method employed, the image datasets are typically processed in various ways prior to training the CNN models, such as image cropping, and image enhancement. The quality of the image data sets greatly affects the model's performance. In the medical X-ray imaging process, the experience of the operator, the patient's own factor and some other reasons that may cause the imaging effect are not ideal, such as low brightness, low contrast, and poor or blurred detail. One research showed that image pre-processing is important when training CNN models, which can effectively boost the performance of CNN models in classification [16]. Moreover, the enhancement of images is a very important part of pre-processing. Hence, research into the relationship between image enhancement and the CNN model is important.

The objective of this work is to evaluate the effect of a pre-processing approach (UM [17]) on the use of pre-trained CNN to detect TBC disease. The UM algorithm has proven to perform well on medical images [18] [19]. Because of its outstanding accuracy and robustness, we use ResNet [20] as a deep learning architecture. The most important contributions of this work are as follows:

- Presentation of a comparative analysis of the performance of ResNet after training of enhanced image datasets through UM algorithm.
- In addition, several fine-tune parameters, including enhancement parameters, are also carefully discussed. To our knowledge, this is the first time that any of these contributions have been presented in the literature.

The paper is divided as follows: section 2 explores the dataset and methodology used in the image enhancement step. Section 3 explains the proposed final detection pipeline and its results.

II. PROPOSED METHOD

A. Dataset

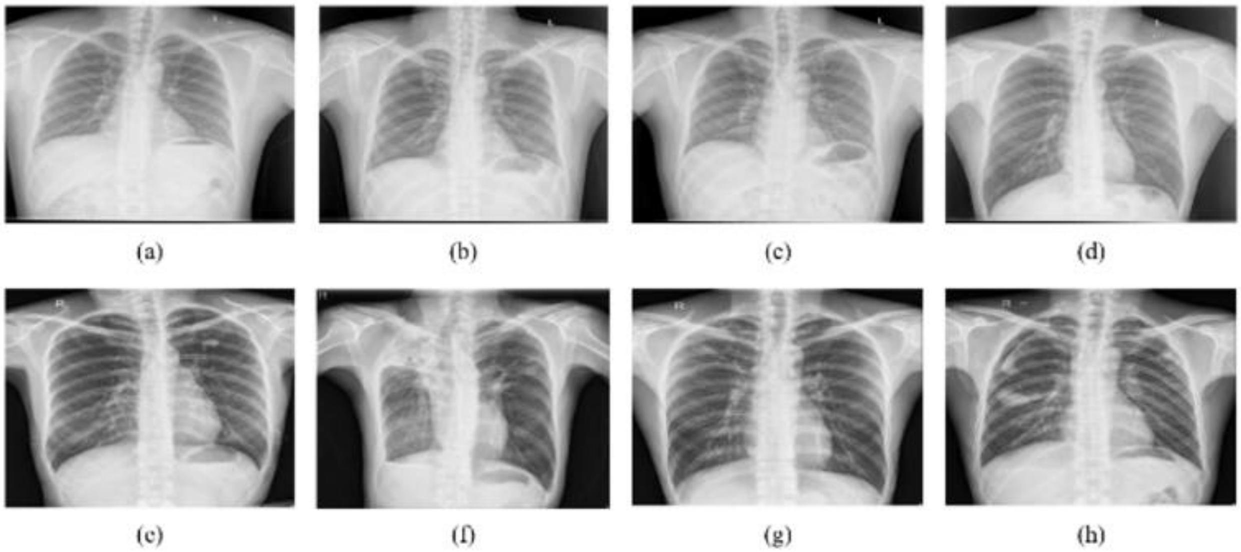


Fig.1. Example of CRs in the Shenzhen dataset. (a) a 28 year-old male, (b) a 39-year-old male, (c) and (d) two 38-year-old males (no TBC). In addition, (e) a 28-year-old female (left secondary Pulmonary tuberculosis (PTB)), (f) a 50 year-old male (bilateral secondary PTB with right upper atelectasis; right pleural adhesions; left compensatory emphysema), (g) a 32-year-old male (secondary PTB in the right upper field), and (h) a 41-year-old male (bilateral secondary PTB with right pneumothorax).

All experiments of this work was tested using the Shenzhen Public Dataset [21]. The Shenzhen data set was collected at Shenzhen Hospital, Guangdong Providence, China. The dataset consists of 662 frontal chest radiographs (CRs), 336 of which are infected with TBC, and 326 of which are not infected with the disease. All images have a resolution of about 3,000x3,000 pixels. In Fig. 1, we visualize the example of CR images in this dataset.

B. Methodology

Color images contain rich details and facts, but the color images have low contrast problems and blurred details due to the effect of light, weather, and other factors. The widely used methods for improving images include histogram equalization, low pass filtering, and high pass filtering. The basic principle of histogram equalization is to enhance the image's visual effect by expanding the image distribution's gray scale spectrum in order to accomplish the purpose of improving the contrast. In image enhancement it is typically important not only to change the image's dynamic range but also to highlight the image's details. Color constant image enhancement technology is an image-based method for enhancing visual effects, through digital image computing and transformation to reflect the image color authenticity and enhance contrast.

Using an image enhancement algorithm: UM, we improve the visualization of TBC x-ray images before deep learning classification stage. The method is independently executed and evaluated. Fig. 2 shows the illustration of the image enhancement step:

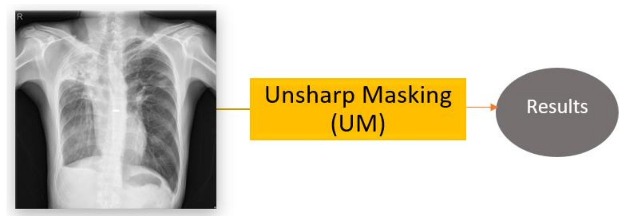


Fig.2. Image processing of gray images

Unsharp Masking

UM [17] is an image sharpening technique that produces a mask of the original image using a distorted, or "unsharp," negative image. The unsharp image is then combined with the original positive image, creating a less blurred image than the original image. In other words, UM is a linear filter capable of amplifying an image's high-frequencies.

The first step of the algorithm is to copy the original image and apply Gaussian blur to it. The radius is an important setting when performing Gaussian blur. Radius is related to blur intensity as it defines the size of the edges.

$$G(i,j) = \frac{1}{2\pi\sigma^2} e^{-\frac{i^2+j^2}{2\sigma^2}} \quad (1)$$

where, i and j are the distance from the origin in the horizontal and vertical axis, respectively. In addition, σ is the standard deviation of the Gaussian distribution.

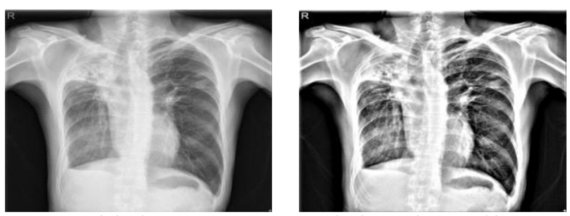
Next, we subtracted the blurred image from the original image, and we will only get the blurred edges. This is what we called the "unsharp mask." Finally, after applying the following equation, the enhanced image is collected:

$$I_{um\_sharpened} = I_{ori} + \text{amount} * (I_u) \quad (2)$$

where, $I_{um\_sharpened}$, I_{ori}, and I_u are final result after applying UM algorithm, the original image and unsharp image, respectively. To be clear, the radius and the amount (in Eq.(2)) are described below:

- **Amount** can be thought of as how much contrast is added to the edges (how much dark or light it will be).
- **Radius** influences the size of the edges to be improved or how large the edge rims are, so a smaller radius improves the accuracy of smaller scale.

The best values for radius and amount, respectively, are 5&2, and 15&2 in our experiment on TBC x-ray images. Fig.3 provides an illustration between the original image and the sharpened image by UM:



Original Image Final UM sharpened image Radius: 15, Amount: 2

Fig. 3. Illustration of the image comparison between original image and sharpened image through UM.

Pre-trained ResNet-50 model

The experiment selected the ResNet-50 model in transfer learning. ResNet [20] is a neural network that uses skip connections to leap over several layers. The purpose to leap over layers is to prevent the issue of vanishing gradients by reusing activations from the previous layer before the neighboring layer knows its weights. The efficiency of the extracted features on the network depends on the depth of the architecture. The ResNet-50 consists of different layers where each layer is normally added multiple times. It assumes that the input is in the form of 3D images, which allows the network to add those properties.

Throughout training, specific parameters are configured in the Conv layers to extract meaningful features from the original input images, while the collection of parameters to be learned in the FC layers classifies the extracted features in the target classes (normal image or TB image). Conv layers acquire visual features in a hierarchical way from raw input images in such a way that lower layers extract low-level features, such as shapes or edges, while higher layers extract high-level visual features, such as part of objects. The labels on the images are given as vectors containing the value '1' for the TB image and '0' for the other. A 224x224 crop is randomly sampled from an image or horizontal flip, with the mean subtraction per pixel. In addition, the standard color augmentation is used. In table 1, we show the parameter used in the training stage:

Table 1: Parameter used in the training stage.

No.	Parameter	Value
1	Batch Size	6
2	Num of workers	10
3	Max Epoch	10
4	Learning rate	0.01
5	Learning rate decay	0.5
6	Learning rate stepsize	3
7	Weight decay	$1x10^{-5}$
8	Crop scale	3.5
9	Image Size	224

Note that for the design of the ResNet-50, each 2-layer block in the 34-layer net is replaced by a 3-layer bottleneck block [20].

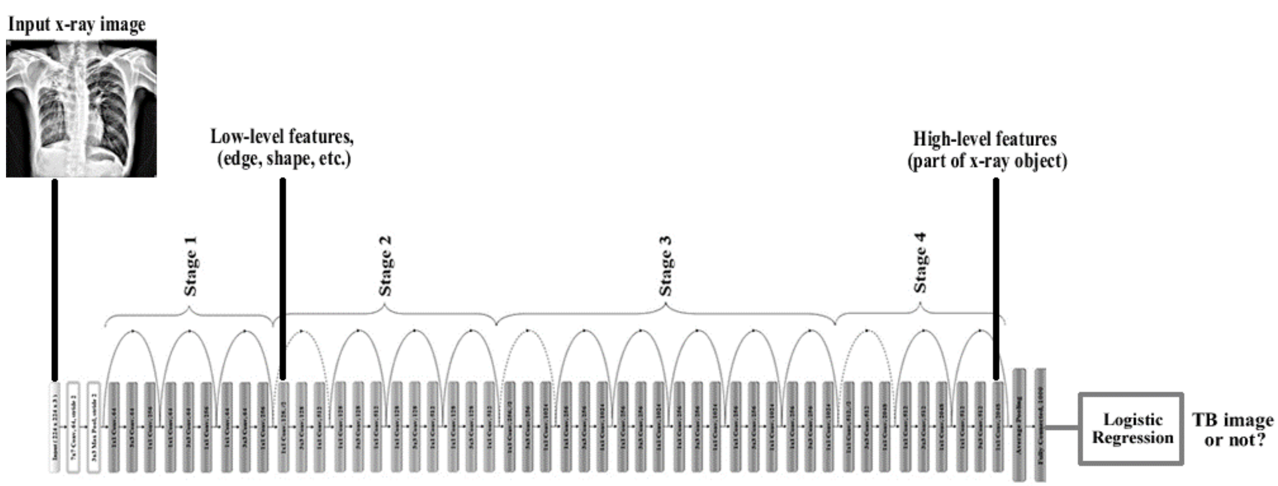


Fig. 4. Proposed CNN architecture for TB detection.

III. Results and Discussion

Using Shenzhen x-ray images as a dataset, experiments with the ResNet-50 model were performed using UM image enhancement algorithm. As thoroughly discussed by Lopes and Valiati, the ResNet model can outperform other models on Shenzhen public datasets. Due to data variance, several orders

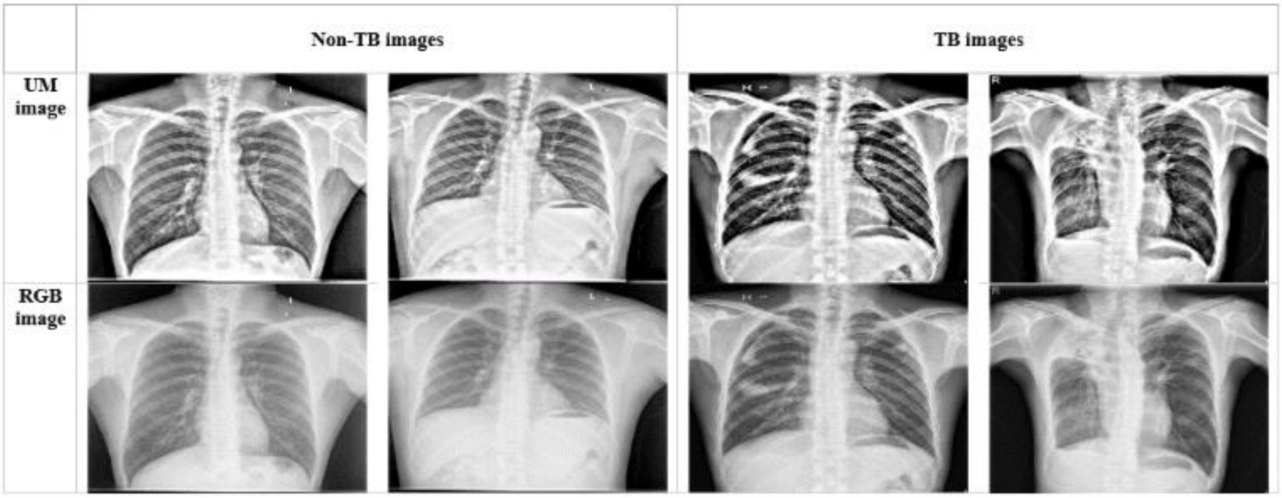


Fig. 5. Some example of testing images during experiment.

of magnitude are smaller and there seems to be no need for very large networks to boost performance [12].

Therefore, in this experiment, we focus on evaluating the effect of image enhancement on the ResNet-50 model. As the sizes of the original images are large and distinctive, the length and width of the images are resized to 640x480. The overall accuracy is achieved by analyzing 10 random test images (both with and without TB). Training images are divided into a batch of size 6. The architecture has been trained for 10 epochs. When we enhance training images, the image contrast is increased, the disparity between the TB area observed and the remaining regions is more noticeable. In comparison, the outline and the edge of the region observed are more distinct. Therefore, when training is carried out in the ResNet-50, as CNN automatically performs the extraction of features, the color and contour details of the region can be better obtained. We compare our proposed pipeline with the work from Lopes and Valiati [12], and ResNet-50 without the enhanced image. The results show that our proposed ResNet-50 with UM enhanced image can outperform other methods, by obtaining 88.69% and 96.15% of classification accuracy and AUC (Area Under Curve) scores, respectively.

Table 2: Accuracy of proposed ResNet-50 with UM image, ResNet-50 with original RGB image, and the method from Lopes and Valiati [12]

	ResNet-50 with UM		ResNet-50 with RGB	Lopes and Valiati [12]
Parameter	Radius: 5, Amount: 2	Radius: 15, Amount: 2	-	-
Shenzhen Datasets	88.69%	83.71%	75.41%	84.7%

Table 3: Comparison results obtained through AUC

	Lopes and Valiati [12]	Our approach (ResNet-50 with UM)
Shenzhen Datasets	92.6%	96.15%

IV. Conclusions

Incorporating deep learning technique with Unsharp Masking (UM) image enhancement, this paper uses ResNet-50 to train the TB images and improve the detection accuracy. The experiments show that the accuracy of the proposed idea can outperform the ResNet with original RGB images. Moreover, we also thoroughly compare the results with previous work that in terms of accuracy and the AUC, the proposed idea can achieve better results. Therefore, the use of an image enhancement method to pre-process the TB images can make the ResNet-50 learn a better model. Future works will evaluate more image enhancement techniques in order to show a more significant effect of enhancement on deep learning models. Moreover, a comprehensive subjective judgment and preference from the medical expert will also be analyzed.

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