Image Enhancement for Tuberculosis Detection Using Deep Learning

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Abstract

Tuberculosis (TB) causes 1.5 million deaths annually. This study evaluates the effect of image enhancement techniques—Unsharp Masking (UM), High-Frequency Emphasis Filtering (HEF), and CLAHE—on TB detection using deep learning (DL). Using pre-trained ResNet and EfficientNet models, enhanced images achieved 89.92% accuracy and 94.8% AUC on the Shenzhen dataset.

Introduction

Tuberculosis (TB) causes 1.5 million deaths annually, and its detection is challenged by low-quality chest X-rays (CXR). Deep learning (DL) models like convolutional neural networks (CNNs) can aid detection but are limited by poor image quality. Traditional methods are expensive, while alternatives lack sensitivity. This study explores how image enhancement techniques—Unsharp Masking (UM) and High-Frequency Emphasis Filtering (HEF)—can improve CXR clarity and enhance the performance of pre-trained ResNet and EfficientNet models for more accurate TB detection.

Methodology

This methodology uses deep learning techniques for image enhancement to improve the accuracy of tuberculosis detection from chest X-rays, aiming to assist in better diagnosis and early detection.

1. TB CXR Image Enhancement

Chest X-ray (CXR) images are enhanced using Unsharp Masking (UM) and High-Frequency Emphasis Filtering (HEF). UM sharpens images by amplifying high frequencies, while HEF enhances fine structures. Histogram Equalization improves contrast but may lead to information loss. These methods were evaluated before deep learning classification, with future work exploring CLAHE to examine over-enhancement effects.

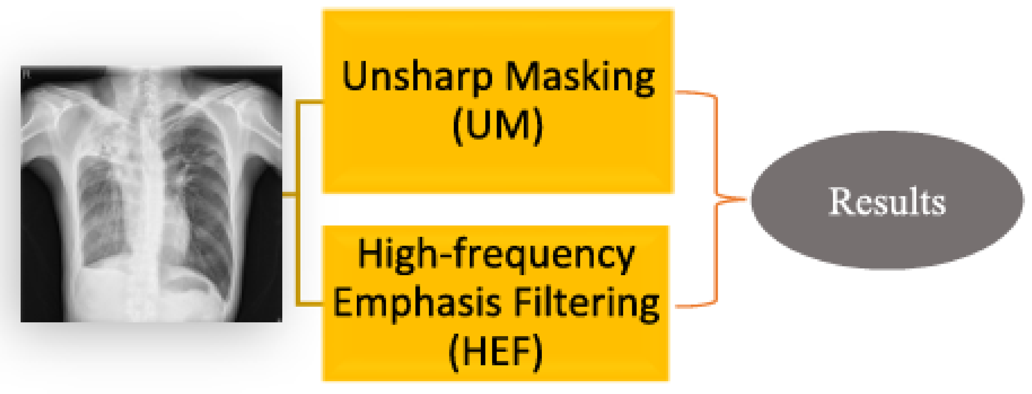

Figure 1. Image processing of gray images.

2. Unsharp Masking (UM)

Unsharp Masking (UM)[1] enhances image sharpness by emphasizing edges and fine details. It works by subtracting a Gaussian-blurred version of the original image, isolating high-frequency components. The enhanced image is obtained using:

$$I_{um\_enhanced} = I_{ori} + \text{Amount} \times I_{unsharp}$$

where I_{ori} is the original image, $I_{unsharp}$ is the computed mask, and Amount controls sharpening. Optimal parameters (Radius = 5, Amount = 2) help enhance TB-related features in CXR images for better clarity.

3. High-Frequency Emphasis Filtering (HEF)

HEF[2] enhances edges by emphasizing high-frequency components using a Gaussian high-pass filter and Fourier transforms.

Gaussian High-Pass Filter:

$$G_{\text{Filter}}(i,j) = e^{-\frac{D^2(i,j)}{2D_0^2}}$$

Fourier Transform:

$$F(i,j) = \sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x,y)e^{-j2\pi\left(\frac{ix}{M}+\frac{jy}{N}\right)}$$

Inverse Fourier Transform:

$$f(x,y) = \frac{1}{MN}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1} F(i,j)e^{j2\pi\left(\frac{ix}{M}+\frac{jy}{N}\right)}$$

Histogram Equalization:

$$I_{\text{hef\_sharpened}} = (I_{\text{ori}} - G_{\text{Filter}}) + \text{Hist\_Eq}$$

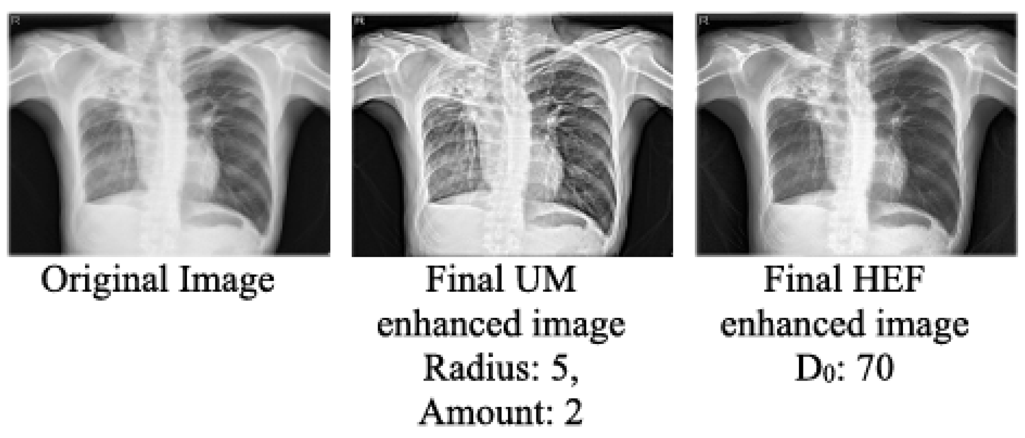

Figure 2. The image comparison between original TB CXR, enhanced UM, and enhanced HEF images.

Methodology

4. Pre-Trained ResNet and EfficientNet Models

Transfer learning with ResNet-18, ResNet-50[3]., and EfficientNet-B4[4] is used for TB classification in CXR images, leveraging pre-trained features to improve accuracy and reduce training time.

CNN and Feature Extraction: CNNs process grayscale CXR images, extracting features via convolutional layers, with fully connected layers handling TB vs. non-TB classification.

ResNet: Uses skip connections to prevent vanishing gradients, enabling deep networks like ResNet-50 to extract complex patterns.

EfficientNet: Employs compound scaling for better accuracy with fewer parameters.

Preprocessing and Training:

- **Image Resizing:** CXR images resized to 640×480 before enhancement, 224×224 for model input.
- **Transfer Learning:** Pre-trained models fine-tune only the final classification layer.
- **Data Normalization:** Per-pixel mean subtraction centers pixel values.
- **Data Augmentation:** Cropping and flipping improve generalization.

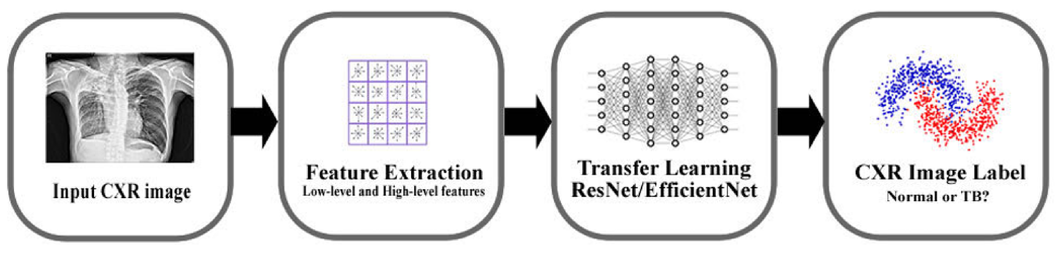

Figure 3. The deep learning-based architecture for TB detection through ResNet and EfficientNet-B4.

5. Enhanced Image Quality Assessment and Parameter Setting

Image Quality Assessment (IQA): IQA ensures enhancement improves clarity without unnatural distortions.

Lightness Order Error (LOE): LOE[5] measures unnatural contrast changes, with lower values indicating better enhancement.

Optimization: Parameters (e.g., radius, amount) are tuned to minimize LOE, balancing clarity and detail preservation for TB detection.

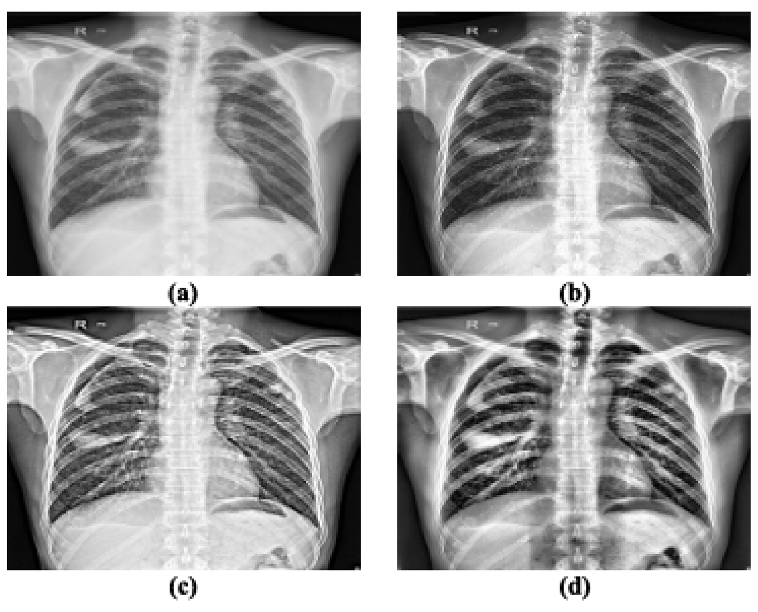

Figure 4. An example of enhanced image and its LOE Score. (a) Original Image, (b) HEF (LOE 341.09), (c) UM (LOE 837.89), and (d) CLAHE (LOE 1852.1).

Experiments and Results

1. Dataset

The experiments in this research use the Shenzhen Public Dataset[6], collected at Shenzhen Hospital, Guangdong, China. It consists of 662 frontal chest X-ray images (336 TB-infected and 326 non-infected), all with a resolution of 3K x 3K pixels. The images were captured using a Philips DR system in September 2012 and have corresponding radiologist readings as ground-truth.

Table 1. Best Parameters for HEF, UM, and CLAHE

Method	Parameter	LOE Score
HEF	D0: 70	**341.09**
UM	Radius: 5, Amount: 2	837.89
CLAHE	Window size: 100 Clip Limit: 150	1852.1

Important Point

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Experiments and Results

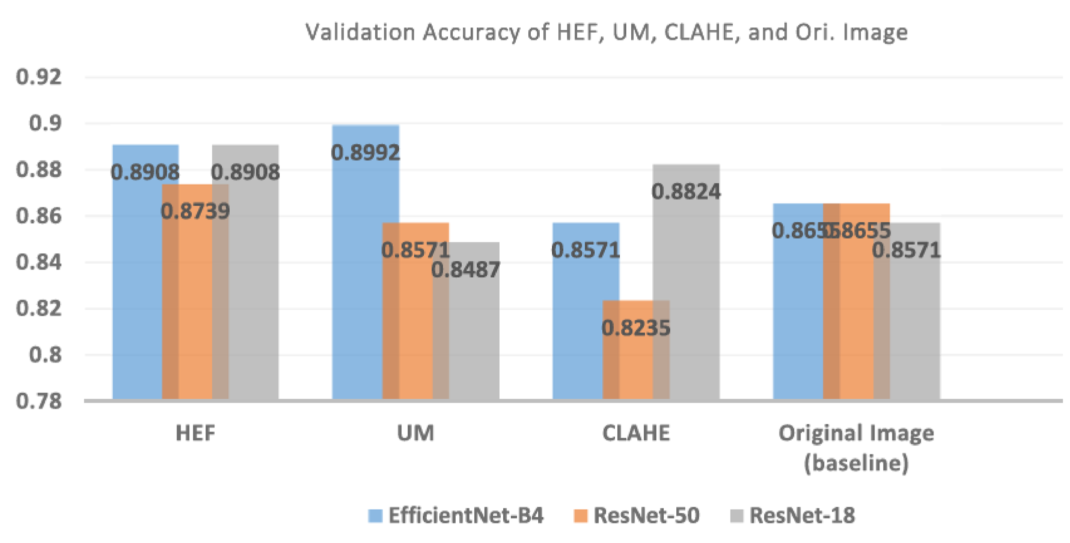

Figure 5. Validation accuracy of each image enhancement method through transfer learning.

2. Image Enhancement and Model Performance This section evaluates the impact of image enhancement techniques—HEF, UM, and CLAHE—on TB detection using CXR images:

a. Lightness Order Error (LOE) Score HEF showed the best LOE score, maintaining natural image quality, while CLAHE reduced performance.

b. Model Performance EfficientNet-B4, ResNet-50, and ResNet-18 were used on the Shenzhen CXR dataset. HEF and UM yielded better validation accuracy than CLAHE, with EfficientNet-B4 performing best (Fig.5).

c. Comparison with Previous Works EfficientNet-B4 with UM achieved 89.92% accuracy and an AUC of 94.8%, surpassing previous methods. Ensemble methods achieved better AUC but are computationally expensive.

d. Computational Performance Training took 14 minutes on a NVIDIA GeForce GTX 1050 Ti with 4GB memory, with inference taking less than a minute per image. Down-sampling images to 224×224 pixels reduced memory usage but may affect accuracy for subtle findings[7].

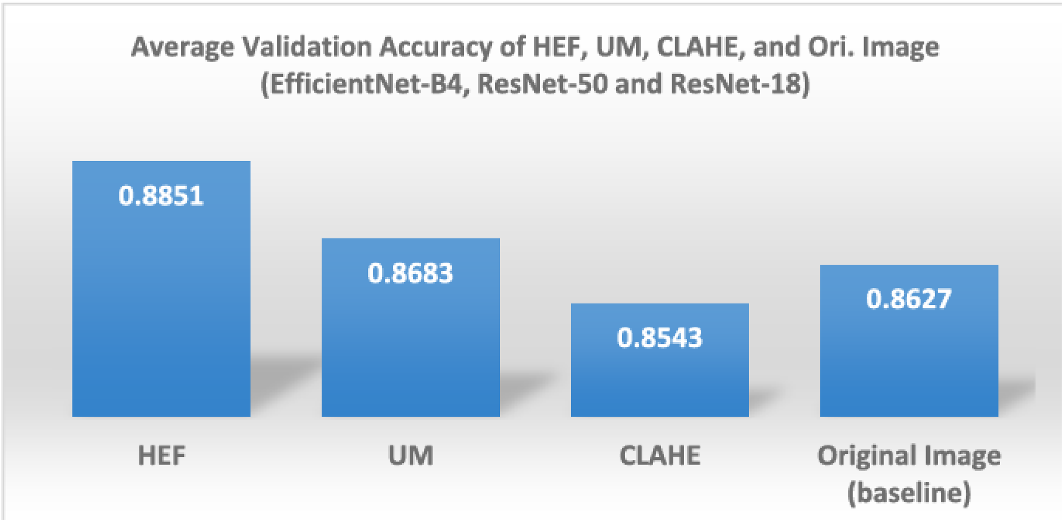

Figure 6. Average validation accuracy through transfer learning (pre-trained of EfficientNet-B4, ResNet-50 and ResNet-18 models).

Conclusions

This research presents a method for tuberculosis detection using deep learning-based image enhancement techniques like Unsharp Masking (UM) and High-Frequency Emphasis Filtering (HEF). By employing EfficientNet-B4, ResNet-50, and ResNet-18 models, the approach improves detection accuracy, with better performance in terms of accuracy and AUC compared to previous works. The use of image enhancement during preprocessing helps pre-trained networks learn better models. Future work will explore additional image enhancement techniques and integrate expert medical feedback. Furthermore, the impact of different enhancement parameters on classification performance will be systematically analyzed. A larger dataset with diverse imaging conditions will also be considered to improve model generalization.

References

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