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A Review on Detection of Tuberculosis using Deep Learning Techniques

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ABSTRACT

Every year, approximately 1.5 million people die from tuberculosis (TB) or get newly infected. It is one of the biggest health problems today. When detected early, the deaths can be prevented; however, its diagnosis is difficult from chest X-rays (CXR) because of the decreased contrast in the images. The promise of using deep learning (DL) techniques in TB diagnostic automation has recently resurfaced; however, they are not woven into the fabric of empirical real-world image datasets in order to achieve optimal performance. In this study, image quality enhancement of CXR images was studied as a solution to improve the performance of deep learning. An experiment was carried out on three imaging enhancement techniques: Unsharp Masking (UM), High-Frequency Emphasis Filter (HEF), and Contrast Limiting Adaptive Histogram Equalization (CLAHE) to enhance images from TB. The pre-trained deep learning models ResNet and EfficientNet were then used for transfer learning to analyze enhanced images. It turned out that image enhancement techniques produced classification accuracies of 89.92% and 94.8% for tuberculous detection, in addition to impressive scores of Area Under the Curve (AUC). The results were obtained from a publicly available Shenzhen TB dataset, indicating an image enhancement technique that could significantly augment the performance of such DL models for TB detection.

INTRODUCTION

For a while yet, tuberculosis (TB) remains the number one infectious disease killer across the globe. Millions yet die from the disease each year despite inputting considerable resources in medical research and diagnostics. WHO, in its 2018 report, attributed about 1.5 million deaths from TB to the disease itself, especially affecting places which include Southeast Asia and Africa. Tuberculosis is caused by the bacterium *Mycobacterium tuberculosis* and spread mainly through droplet spray-form transmission via coughing or sneezing by an already infected person. Currently, there are available methods of diagnosis including molecular analysis and bacterial cultures but most of them are very expensive and not readily accessible in resource-poor settings which are usually the most affected by TB.

A most simple TB diagnostic method is sputum smear microscopy. It is quite cheap, widely available, and relatively easy to perform. Most importantly, the sensitivity of this method is limited; it will not detect TB in all cases, especially in patients with low mycobacterial loads or very early in the course of the infection. Hence, there is greatest need for improving existing diagnosis or developing new ones for TB in clinics, particularly in resource-limited countries where the highest prevalence still prevails.

Over the years, AIs and MLs have been able to prove their great possibilities for improving accuracy in medical diagnosis so far-as tuberculosis. One important type of this new machine learning revolution is DL-deep learning. Here algorithms can learn from the massive data in an incredible way in all types of applications, be it pattern recognition or prediction. A variant type of DLM- CNN or convolutional neural networks-well targets image recognition. Recently, application of this model in medicine is increased with TB detection through chest X-rays (CXR), one of the most widely used diagnostic tools for tuberculosis.

Deep learning aspires to deliver high output in TB diagnosis. Compared with Enterprise Software Development Goals, deep learning (DL) techniques bring more innovative approaches to the entire society and then improve fulfillment in many other areas. From facial recognition to autonomous driving-in fact, deep learning, particularly in the case of convolutional neural networks (CNNs), has become really successful in quite a few image-based tasks. These diagnostic applications include disease detection in medical imaging. While several reports have claimed good results from using DL-based systems for TB diagnosis, not much progress has been made in terms of developing a fully operational system. Preliminary studies have been hampered by a number of challenges, most being referred to as limitations in data sets or poor imaging quality.

With reference to TB, one of the key difficulties is related to the chest X-ray (CXR) image quality which often tends to have low contrast, degraded resolution, or even blurriness-making it obscure to any early stage/tiny signs of infection. Generally, both human radiologists and automated systems find it very difficult to pick an early case or understand minute details that might affect the diagnosis. Therefore, it is likely that enhancing images with pre-processing techniques is critical for boosting the model performance of the DL approaches for TB detection.

- Image Pre-processing for the Optimized Performance

Image pre-processing includes steps such as refining an image because raw images have less quality than built-in images and are fed into a deep learning model for analysis. Pre-processing is indispensable for medical images, especially chest X-rays which are necessary for the detection of TB, because poor brightness, low contrast, and blurriness can all create problems while using the DL model for identifying those features which are very important for accurately diagnosing the disease. Image enhancement is one of the pre-processing activities that makes certain features subtle in the image clearer and therefore improves the model's prediction.

To improve the image, there are two most common techniques that are really in-use nowadays: Unsharp Masking (UM) and High Frequency Emphasis Filtering (HEF). These two techniques tend to modify the contrast and sharpness of the images for improving a specific feature of an image. The only thing actually differing them was that UM sharpens the image by subtracting a blurred version from it for building its final output sharper while HEF enhances its high-frequency components in the image so that edges and finer details would become more apparent.

Various works have proved the appropriateness of both techniques with regard to enhancement of medical images. It has been successfully applied in the fields ranging from detection of various lung diseases to tumor recognition. More recent works have highlighted these techniques in improving chest radiography (CXR) images for better presentation to the deep learning models.

There exists a deep learning model for tuberculosis diagnostic, that is, the ResNet and EfficientNet models. Both models are known to be very effective in image classification tasks thus could be very helpful in TB detection from CXR images. ResNet is the best matching technique with residual networks deep neural networks having skip connections between the layers so that deep learning could build its model more efficiently while avoiding the vanishing gradient of extremely deep networks. So ResNet has been used satisfactorily in medical image analysis with very high accuracy in all sorts of image classification tasks.

On the contrary, EfficientNet is a recently introduced model that emphasizes maximizing the accuracy and efficiency of neural networks. Balanced depth, width, and resolution through a compound scaling method yield high performance while maintaining a low parameter count. That is why EfficientNet currently exhibits state-of-the-art performance in terms of image classification, making it one of the brightest candidates for medical imaging analysis regarding TB diagnosis

- The Role of Transfer Learning:

From the beginning to the utmost end with deep-learning models going through training by large amounts of well annotated data for almost all the tasks like that for deep learning applications. This, however, may not serve some applications like this one, especially when put into practice for rare diseases as tuberculosis (TB). Indeed, in most cases, the number of TB-marked data has declined very much; hence several deep learning algorithms may not perform well due to low sample sizes. It is transfer learning that comes up in such situations. Transfer learning is a process where we have some kind of pre-trained model. For instance, it might have been built on a very large dataset like ImageNet; it is finetuned to work on this task at hand, which is a TB CXR dataset. It brings all the so-called learned knowledge-from those huge datasets-into application in our pretty specific task, which is TB detection. Transfer learning is very important in medical image classification because it increases the effectiveness of deep learning models with less data.

- Objective of the Study:

The primary objective of this research paper is to explore the impact that image enhancement techniques have on the performance of pre-trained deep-learning models in relation to tuberculosis detection. More specifically, this investigation is intended to examine the impact of Unsharp Masking (UM) and High-frequency Emphasis Filtering (HEF) on the accuracy levels of TB detection when these techniques were applied to CXR images. The discussed techniques would improve images before sending them to pre-trained CNN models like ResNet and EfficientNet to fine-tune them using a TB dataset.

The hypothesis is that image enhancement techniques improve the performance of deep learning models in TB detection. In this regard, the use of CXR images, usually of low contrast and poor quality, might also improve capture in the context that TB infection would show such mild changes in the image quality. With better-quality images, models could better capture the weakening subtle features in TB for more exact prediction.

LITERATURE SURVEY

This paper is an effort to combine deep learning with two image enhancement techniques, namely Unsharp Masking (UM) and High-Frequency Emphasis Filtering (HEF), to improve the detection accuracy of TB. The study employs three pre-trained Deep Learning (DL) models: EfficientNet-B4, ResNet-50, and ResNet-18, which had been fed with rebuilt images of TB .The results indicated a considerable increase in detection accuracy, which is made as a comparison with previous studies, which itself proves superiority in both accuracy and Area Under Curve (AUC) scores. On the other hand, image enhancement will allow the DL to learn better and perform. Future work will also address further integration of other image enhancement techniques to improve even more in DL models. There will also be evaluation from the medical expert about the subjective assessment and preference in the enhanced images and the performance of the model.

METHODOLOGY

1. Techniques for image enhancement:

- Unsharp Masking (UM):

- A sharpening technique that makes use of a Gaussian blur to generate an "unsharp" mask.
- The image could then be generated by summing the original and unsharp mask using the equation:

  Ium_enhanced = Iori + amount × Iu.

- Parameters:
  - Radius: controls the size of edges.
  - Amount: usually controls the contrast that is added to edges.

➢ High Frequency Emphasis Filtering (HEF):

- High-pass Gaussian filter is used for the sharpening of edges.
- The filtering process is through Fourier transform, filtering in frequency domain, followed by inverse transform.
- It uses histogram equalization (Hist_Eq) applied after filtering for improvement in contrast.
- Enhanced images are given by:

  Ihef_sharpened=(Iori+GFilter) ×Hist_Eq.

2. Inference preprocessing image:

- Input CXR images went through a process of resizing into 640 × 480 pixels.
- Then resized into 224 × 224 pixels to fit in the pretrained deep learning models.
- This step was followed by per-pixel mean subtraction for normalization.

3. Deep Learning Models:

- Pre-trained Models:
  - ResNet-18, ResNet-50: To apply skip connections.
  - EfficientNet-B4: Reducing parameters and improving prediction effectiveness.
- Feature extraction through convolutional layers classifying outputs with fully connected layers.
- Binary Classification for TB detection: Labels are 1 for TB and 0 for normal.

4.Comparative Studies: -

- The proposed methods have shown substantial improvements when applied to comparison techniques with respect to baseline methods (which did not use image enhancement). -
- Highlighted by the bar charts (Fig. 10-13) was the superior performance of the proposed approach.

5.Computational Efficiency: -

- Training Time: 14 min on NVIDIA GeForce GTX 1050 Ti (4GB).
- Inference Time: under 1 minute for each image.
- Framework: PyTorch 1.2.

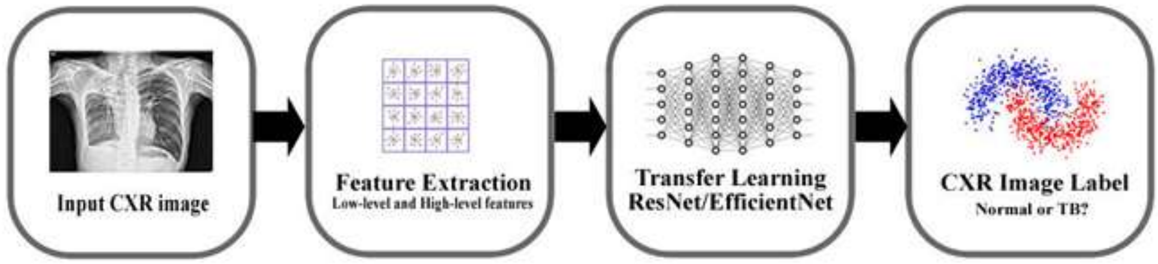
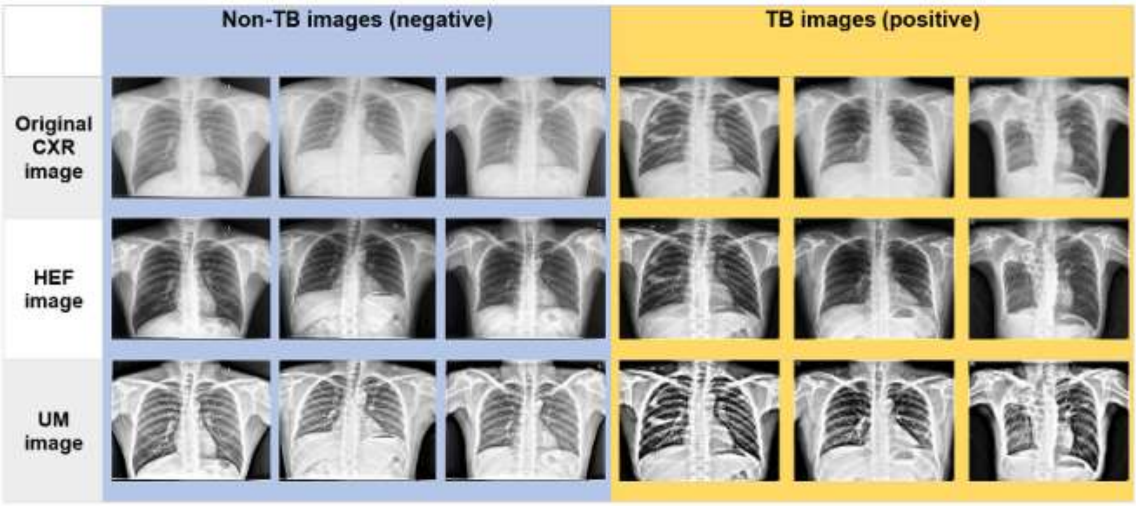


FIGURE 7. The deep learning-based architecture for TB detection through ResNet and EfficientNet-B4.



MODEL DISCRICPTION

1.Convolution Neural Network (CNN):

Convolutional neural networks are modern learning techniques to picture or image data or even visual media such as video. CNNs are built with numerous layers, including convolutional layers, pooling layers, and fully connected layers. At each stage, the unit performs activity through processing units to extract attributes produced by the input data. These layers incorporate layers for pattern detection with filters or kernels, dimensionality reduction while retaining salient features, and classification or regression on the extracted features. CNNs have been used widely for image classification and detection and ad hoc applications in medical diagnostics. They are, indeed, well suited to tasks of the visual kind because of their superiority in modelling spatial hierarchies and patterns within data.

2.Resnet:

ResNet comprises the residual neural network trained to solve fading gradients while training with a deep network architecture. In its structure, skip connections are formed so that a layer could skip the next and activate the one from previous layers. This design are argumented feature extarction and moreover have been linked in gradients such good utilization and improvement. Its core structure consists of convolution, pooling and fully connected layers, with what has been denominated "residual blocks." Each of the blocks of the block has a shortcut path directly adding the input to the output of the stack of layers for easier optimization. Such models include ResNet-18 or ResNet-50 which really is quite superior when it comes to medical imaging or even classification task because of how robust and scalable they can go.

Thus ResNet (Residual Network) is a deep learning architecture to countervanishing gradients in very deep networks. It possesses skip connections so that layers can skip the one next to them and reuse those activations from previous layers. The design improves feature extraction and promotes the best gradient flow. ResNet consists of convolutional, pooling, and fully connected layers, with its main structure made up by so-called "residual blocks." Each block thus contains a shortcut path which directly adds the input into output produced at the end of a layer stack to be more comfortable optimizing. Models, such as ResNet-18 or ResNet-50, indeed are very effective as far as medical imaging and even tasks like classification are concerned because of their strength and scalability.

3. Efficientnet:

The EffcientNets are a family of deep-learning models offering higher accuracy while working on lower computation times through a compound scaling between depth, width, and resolution dimensions. These models range from B0 to B7 and are derived from an original base known as EfficientNet-B0 using neural architecture search. The compound scaling provided in EfficientNet gives a lesser number of parameters and FLOPS maintaining a much higher precision for effective operations from many of the traditional models. A special area application is in medical imaging tasks, such as tuberculosis detection. It is the most capable modality of extracting features from sensitive enhanced images much more stably than others. EfficientNet-B4 has been shown in studies to yield accuracy competitive with that of other techniques employing image enhancement, along with Area Under Curve performance.

RESULTS

1. LOE (Lightness Order Error) Assessment:

- ❖ Naturalness performance for HEF has been better than other enhancement methods (UM and CLAHE).
- ❖ CLAHE had unnatural enhancement and thus the transfer learning step failed with poor validation accuracy.

2. Model Training and Validation:

- ❖ Data Split: Training: 60% Validation: 40%.
- ❖ Training Details:
  - Error Function: Categorical Cross-Entropy.
  - Optimizer: SGD (Stochastic Gradient Descent) with weight decay (0.00001).
  - Batch Sizes: 6 for ResNets, while for EfficientNets: 2.
  - Epochs: 10.
- ❖ Validation has shown great improvements in accuracy owing to the improved images.

3. Model Performance:

- ❖ With HEF and UM enhancement, EfficientNet-B4 consistently outperformed ResNet-50 and ResNet-18 in stability and accuracy.
- ❖ Efficiency of 89.92% was achieved along with 94.8 AUC by using EfficientNet-B4 with UM enhancement.
- ❖ Had superior accuracy over earlier works from Lopes & Valiati, Jaeger et al., and Hwang et al.
- ❖ Competitive results in relation to those based on ensemble methods of Rajaraman & Antani, although it was not based on ensemble approaches.

4. Comparative Analysis:

- ❖ The proposed methods in this study generated touched bases with the abandonment methods.
- ❖ As shown in Bar Charts (Fig. 10-13) the proposed method has a clear comparative advantage over the other methods margin to margin.

5. Computational Efficiency:

- ❖ Training time: ~14 minutes on NVIDIA GeForce GTX 1050 Ti (4GB).
- ❖ Inference time: less than 1 minute per image. Framework: PyTorch 1.2.

6. Limitations:

- ❖ Down-sampling images to a resolution of 224 × 224 for efficiency purposes is a trade-off in that accuracy suffers, and higher resolutions tend to bring better results-all the more true for the subtle features in photographic images.

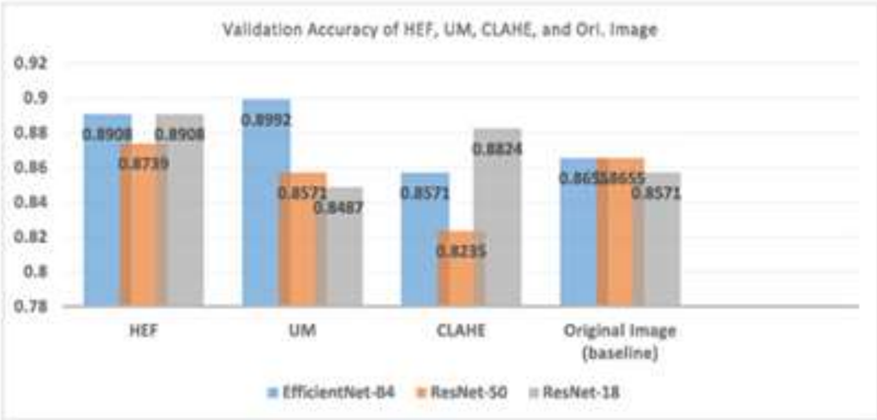


FIGURE 10. Validation accuracy of each image enhancement method through transfer learning.

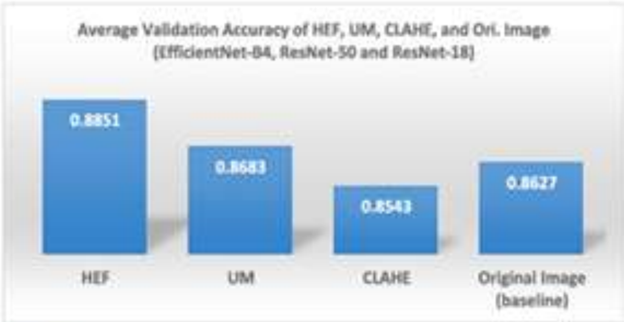


FIGURE 11. Average validation accuracy through transfer learning (pre-trained of EfficientNet-B4, ResNet-50 and ResNet-18 models).

CONCLUSION

This research proves how deep learning not only assists with indicated image enhancement, here using Unsharp Masking and High-Frequency Emphasis Filtering, but also boosts detection performance for TB from CXR images. The proposed pipeline reported remarkably competitive accuracy and AUC scores using pre-trained models such as EfficientNet-B4, ResNet-50, and ResNet-18, and surpassed many prior works.

The forum argued that around enhancement of image features would contribute significantly in improving the performance of deep learning models in selecting and learning better features. The same method not only enhances the performance of models but also provides the base for accurate detection of TB.

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