Screening TB Using Deep Transfer Learning

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***Abstract*— Tuberculosis is a major public health problem and has to be proactive screening for quarantine by means of developing machine learning model to screen suspected case. This can be mutually beneficial to healthcare providers and patients. The application of deep learning technique for medical image classification has been developed and grown exponentially over the past few years. We propose Convolution Neural Network (CNN) model because it is one of several well-known and high performance models for image classification. This research presents neural network to classify chest imaging into 2 classes: normal and tuberculosis. We collect 3 datasets of chest X-ray image: Montgomery, Shenzen and Bureau of tuberculosis. The researchers compared 4 CNN classification models to find out the best model that is suitable for chest X-ray. Performance was measured by using metrics: accuracy, precision, recall and AUC. The result of this study shows that DenseNet model is more accurate than others and we tune the model for the best threshold and train it with Thai Bureau of tuberculosis chest image for screening TB for Thai people. The accuracy for discrimination normal lung and TB-infected lung in the best model is 91% and AUC is 95%. This model would aided healthcare providers for TB screening large population in Thailand.**

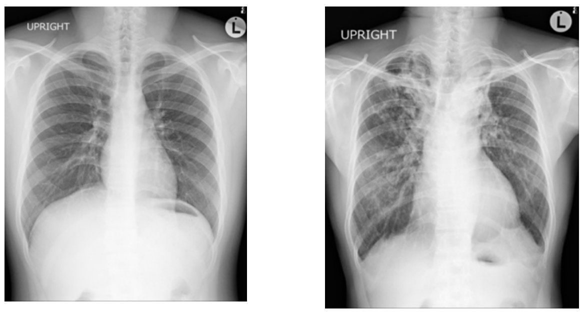
Keywords—Chest X-ray (CXR), Tuberculosis (TB), Convolutional Neural Network (CNN), Transfer learning

I. INTRODUCTION

Pulmonary tuberculosis is an airborne infection disease caused by Mycobacterium tuberculosis. It is a public health problem worldwide and a major cause of morbidity and mortality in Thailand. The World Health Organization has declared tuberculosis a global public health issue. Epidemiological data reveal that major problems with tuberculosis are: The number of TB cases is large and tends to decline more slowly to allow TB to be controlled in the near term. Multidose-resistant TB has a higher number of cases and second-line therapy has low success and high cost. The World Health Organization has classified TB in Thailand as a serious problem. It is an important task to be proactive in finding the infected person for treatment to reduce the infection from normal people who have not yet had the infection [1], [2]. Because it is an infectious disease that is prevalent in Thailand. Due to cost effective and general use of X-ray, developing AI model will help healthcare professionals reducing time and cost for mass screening using chest X-ray.

A. Radiological findings of TB

Characteristics of chest X-ray film show that the lungs appear black because the lungs are airy. Ribs, heart and vessels are seen as white because these organs are high density. Infection or inflammation will appear whiter than normal lungs, sometimes seen as a cavity. The lung with pulmonary tuberculosis contain the specific pattern that can be recognized to diagnose the disease. Pulmonary tuberculosis commonly be found abnormal reticular or reticulonodular infiltration at the upper lobe of the lung [3]. The reason for this may be due to this area contains high oxygen pressure more than other areas in the lung. It occasionally can be found in other sites, including the superior segment of the lower lobe, middle lobe, lingular lobe etc. Pulmonary tuberculosis can give lung radiographic features in several patterns, depending on the pathogenesis of the disease eg. nodular infiltration, fibronodular infiltration, miliary infiltration, consolidation, fibrosis, atelectasis, bronchiectasis and cavity in the lung. A cavity formed in the upper lobe that is not usually found to have an air-fluid level as seen in lung abscess caused by bacteria [4]. Pulmonary tuberculosis chest film pattern is different from normal film as Fig. 1.



Normal film — Tuberculosis film

Fig. 1. Normal and TB Chest film.

B. Deep learning

Deep Learning is an automated learning method of imitating the human brain's processing pattern. It uses a multiple layers neuron-like network (in Fig. 2.) and learn from the sample data. Such information will be used to detect pattern and classify the data.

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The basis of deep learning is an algorithm that attempts to create a model to represent high-level semantics of data. The algorithm builds a data architecture made up of multiple substructures and each of them is derived from non-linear transformations. It can be viewed as a method of machine learning that attempts to learn how to represent data effectively. Deep learning is a highly potent method of handling features for unsupervised learning or semi-supervised learning. It can be roughly divided into two types: Feedforward Neural Network, where data can pass through a processor only one way. A Recurrent Neural Network reuses the previous data to predict future outcomes [5].

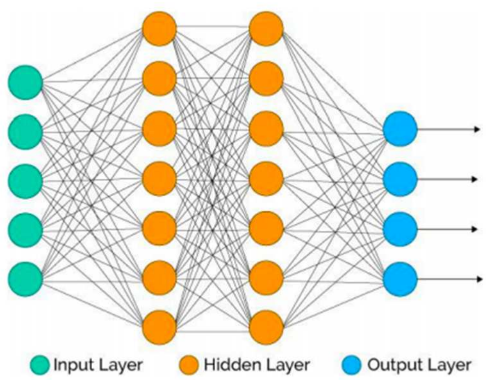


Fig. 2. Neural network.

C. Convolutional neural network (CNN)

The convolutional neural network is a special neural network structure that is capable of classifying image data much better than other neural networks. Main 3 layers of CNN are convolutional layer, pooling layer and fully connected layer as Fig. 3. Convolution layer is the core layer of CNN which can extracts parts of the image by a feature detector, also known as a kernel, so that the model can learn the characteristics of the image effectively and accurately. There are adjustable hyperparameters such as the size of the filter, stride and padding. Pooling layer conducts dimensionality reduction, reducing a number of parameters in the input. The last layer is fully connected layer which compiles the data extracted by previous layers into the final output. There are different types of CNN architectures such as AlexNet, DenseNet, VGG, ResNet, Inception Network etc. [6], [7].

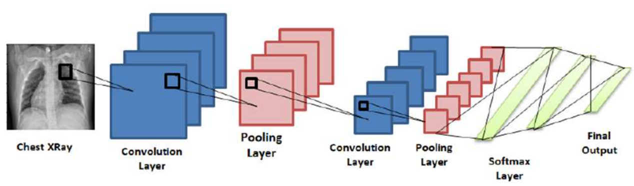


Fig. 3. Convolutional neural network.

D. Tranfer Learning

Transfer Learning is the process of transferring knowledge from a model to be used in a new related problem. It reduces the time usage for model learning. This is different from the traditional machine learning training process that learns input data from scratch. It is useful for learning from examples with various sources and allows the model to learn on small data or limited environments [8]. This can be done through various CNN models such as AlexNet, DenseNet, VGG, ResNet, Inception, EfficientNet etc.

II. RELATED WORK

Usage of deep learning is increasing in various fields of healthcare. Pesapane et al.[9] found the increase in these studies from 100-150 studies during 2010 to 700-800 studies during 2020 with the vast majority of medical artificial intelligence research involved in radiology. The images were obtained from X-ray, ultrasound, CT, MRI including the brain, bone, lungs, gastrointestinal tract etc. Artificial neural network is introduced to classify lung X-ray images by Rahib et al. [10]. They found that neural networks for detection of abnormalities in CXR using CNN is better than other neural networks. There are well-developed models which have different structures as following: Krizhevsky et al.[11] studied and developed deep CNN AlexNet in 2012. Simonyan et al. [12] developed deep CNN VGG in 2014. He et al.[13]] studied and developed deep CNN ResNet in 2016. Huang et al. [14] studied and developed deep CNN DenseNet in 2017. Tan et al.[15] studied and developed deep CNN EfficientNet in 2019. They have proposed improving models based on the CNN structure for different types of image classification. A deep transfer learning technique was applied to these models and pretrained at the upper layer and evaluated them by using Area Under Curve (AUC). Jaeger et al.[16] developed a CNN structure and applied on 2 open datasets: Montgomery and Shenzhen datasets. The result of this study using CNN on both datasets evaluated by AUC were 87% and 90% respectively and accuracy were 78% and 84% respectively. Hwang et al.[17] studied the structure of AlexNet and tested it on the available tuberculosis patient dataset and received AUC 93%. Hashmi et al.[18] studied lung infections by transfer learning on the Resnet18, DenseNet121, MobileNetV2 InceptionV3 and Xception and found that DenseNet121and Resnet18 achieved higher accuracy than the other three models. These CNN structures should be developed and improved further by using open datasets and Thai Bureau of tuberculosis dataset to increase number of data and efficiency of the model appropriate to frequent patterns that found commonly in Thai population. We compare each set on each transfer learning model and determined the proper model that achieves the highest in accuracy and sensitivity.

III. Data

We collect 3 datasets of chest X-ray image from 2 opensource datasets: Montgomery 138 images, Shenzen 662 images and one dataset from Bureau of tuberculosis 943 images (All images are already anonymized.). The details of 3 CXR set are as shown in Table I.

TABLE I. IMAGES IN ALL DATASETS

Source	**No. of images**			
	Train	***Validation***	***Test***	***Total***
Montgomery				
• Normal	56	8	16	80
• TB	40	6	12	58
Shenzen				
• Normal	228	33	65	326
• TB	235	34	67	336
Bureau of TB				
• Normal	306	44	88	438
• TB	353	51	101	505

IV. Method

In this research, we run the software system on keras open-source deep learning framework with TensorFlow 2.6.0 as the backend, python 3.7.11 and hardware GPU: Tesla T4 16 GB GDDR6. We load the pre-trained architectures on the ImageNet Dataset and transfer learning to prepared dataset composed of train, validation and test dataset which is divided by ratio 70%, 10%, 20% respectively with 2 classes (normal, tuberculosis). The layers was used in this model are convolutional layer, max pooling layer and dense layer. The parameters are adam optimizer with learning rate 0.0001. The model is fitted with batch size 32 training, 15 epochs.

A. Data preparation

The data were preprocessed with image augmentation by 5 operations;

- Image adjustment to be black and white
- Random brightness adjustment ± 20%
- Random rotation range ± 10 degree
- Random scaling zoom range ± 10%
- Horizontal image flipping

B. Transfer learning

We compare 4 CNN models: VGG16, ResNet50, EfficientNetB0, DenseNet121 on architecture as Fig. 4. to find out what is the best model for X-ray imaging. To achieve more accuracy, we bring the best model to fine-tuning and train it with all datasets from Bureau of tuberculosis.

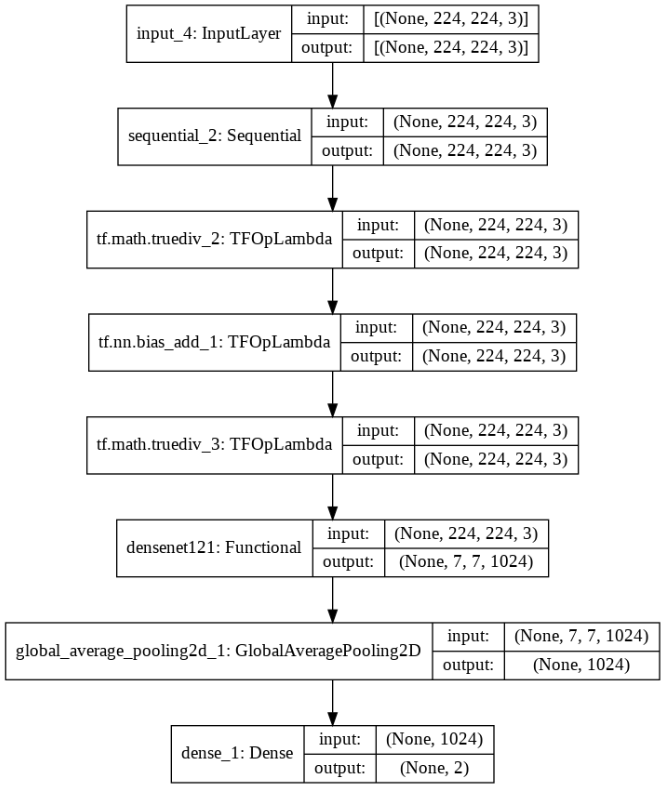


Fig. 4. Model architecture.

V. Results

To test the efficiency of the model, we used deep transfer learning based on 4 models: VGG16, Denset121, Resnet50, EfficientNetB0 and achieved an test accuracy of 64%, 77%, 83% and 77% respectively and AUC 90%, 92%, 93% and 91% respectively.

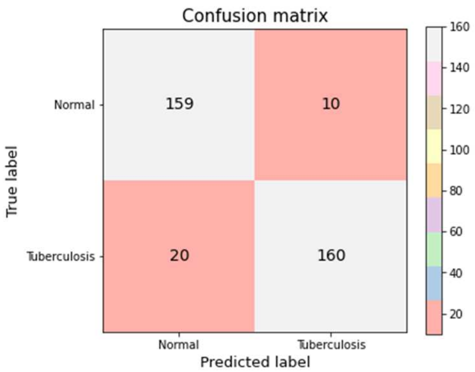
TABLE II. MODEL COMPARISON

Model	**Accuracy**	**Precision**	**Recall**
Densenet121	83	83	83
Resnet50	78	79	78
EfficientNetB0	78	78	78
VGG16	66	72	67

We selected the best model that is DenseNet121 and select the best threshold that gives the best recall (suits for screening) and precision. We train DenseNet model with 3 dataset including Thai Bureau of tuberculosis dataset and then test it on individual datasets and all datasets. The accuracy is increased in every dataset as shown in Table III.

TABLE III. PERFORMANCE OF DENSENET121 TESTING ON EACH DATASET

Test Set	Accuracy	Precision	Recall
Bureau of TB	96	96	96
Montgomery	86	86	86
Shenzen	92	92	92
All datasets	91	91	92

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              precision    recall  f1-score   support

           0       0.89      0.94      0.91       169
           1       0.94      0.89      0.91       180

    accuracy                           0.91       349
   macro avg       0.91      0.91      0.91       349
weighted avg       0.92      0.91      0.91       349
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Fig. 5. Confusion matrix Densenet on all datasets.

VI. CONCLUSION

The Densenet121 CNN architecture achieves good performance in chest X-ray image classification applications. The data from Bureau of tuberculosis are included in order to adapt the model to fit Thai population. This model can be used in many hospitals or prisons for screening TB. We conclude from testing model on each dataset, that the result of Bureau of TB dataset achieves the best score and the next is Shenzen dataset and Montgomery. The accuracies are 96%, 92%, 86% respectively. Therefore, how well the model performs depends on the number of images used to train and may have to adjust the model to suit the task. In this case, we chose the threshold that gave the highest sensitivity(recall) because it would be useful in screening patients with TB. If we want to perform diagnosis, we may change the threshold value that leans towards specificity. Further work for more accuracy and more robustness, more data should be collected and from multiple sources.

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