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A Transfer Learning Approach to Leveraging Pre-trained CNN Models to Detect Tuberculosis using Chest X-Rays

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Abstract

Pre-Trained Deep Learning models[1] are Convolutional Neural Networks that has been developed and bench marked for performing image classificationon a very large dataset such as ImageNet[2]. These pre-trained networks have demonstrated their capability to work well even with images that are not part of the ImageNet[2] dataset through the transfer learning approach[3]. Pre-trained models help us with eliminating the cost and time involved in training a CNN model from scratch. In this paper we evaluate the performance of some ILSVRC[2](The ImageNet Large Scale Visual Recognition Challenge) award winning pre-trained CNN models over the publically available Tuberculosis CXR datasets, we also appraise the ability of these pre-trained models to generalize for tuberculosis detection through CXR images. We customize the pre-trained model as per our requirements and fine tune its performance. The pre-trained CNN models that we have chosen to evaluate on the tuberculosis dataset as a part of this studyare:VGG-16[4] ,VGG-19[4],AlexNet[5], ResNet-50[6], Inception[7] and DenseNet[8].

Keywords : Tuberculosis, Chest X-ray, Deep learning, Transfer learning, Convolutional Neural Network

1. Introduction

As per the World Health Organization (WHO) tuberculosis is ranked as one of the top 3 infectious killer diseases, second only to HIV[9]. It is solely responsible for the death of around 2 million people across the globe every year. According to a study presented by the WHO, for every second the TB bacilli newly infects someone and one in every ten of such newly infected person will become infectious or sick later on in their life. In 1993 the WHO declared TB as a global emergency and this put the spotlight on Tuberculosis in the world stage.One of the key diagnostic tools for screening Tuberculosis infection in lungs is through chest radiography popularly called as chest X-Ray (CXR)[10].Transfer learning is a ML approach where a model trained on one work is rehashed on another related work. Using transfer learning, we exploit the knowledge gathered in a particular context by generalizing it on another context and thereby reducing the training cost.In this learning paradigm we limit the purview of a potential model without compromising its capabilities and fit it on an entirely different but related problem.Pre-trained CNN's have time and again demonstrated that they have the ability to work well even with images that are not part of the ImageNet dataset through the transfer learning approach. We can customize the pre-trained model as per our requirements and fine tune its performance.

In this paper that we have chosen to evaluate the tuberculosis dataset on VGG-16[4] ,VGG-19[4],AlexNet[5], ResNet-50[6], Inception[7] and DenseNet[8]. All these pre-trained CNN's are award winners in the ImageNet challenge and have a well-established performance. In the first stage of the experiment we evaluate these CNN's performance as classifiers over our TB Dataset. We identify the CNN that gives us the best classification result, we choose this as the optimum model for the second stage of the research. In the second stage of the experiment we employ the train and freeze approach of transfer learning, wherein we freeze some layer of the chosen CNN model and observe its performance.

2. Related Work

In the recent years CNN's have made great progress in the field of medical image processing, in this section we will discuss some of the recent works that use CNN for tuberculosis diagnosis. Hwang et al.obtained an accuracy of 90.3% and AUC of 0.964 using transfer learning from ImageNetwith a training dataset of 10848 chest X-rays [11]. Lakhani &Sundaram usedGoogLeNet and AlexNetfor classification of tuberculosis infected CXR's [12], pre-trained AlexNetachievedan AUC of 0.98 and GoogLeNet achieved an AUC of 0.97. Lopes and ValiatiusedGoogLenet, ResNet and VggNetmodels aspure features extractors and utilized SVM as the classifier, they achievedAUC of 0.900[13]. Sahlol et al. [14] used CNN as fixed feature extractor and ArtificialEcosystem-Based Optimisation to select the optimal subset of relevant features. KNN was usedas the classifier.Islamet.al have used fine-tuned ResNet-50, ResNet-101,ResNet-512, VGG16, VGG19 and AlexNet to identify tuberculosis infection and they achieved an AUC of 0.85–0.91 [15]. NIH-14 dataset [16]. Contains images with a wide variety of chest infection but it does not have CXR's with TB but the modality of the data is the same, and some studies have utilized models trained on this dataset for tuberculosis prediction.Yadav et al. [17], split the dataset as per the resolution and quality of the images, the proposed model was first trained on the low resolution NIH dataset and then trained on the TB dataset. Transfer learning approach has also been used by Abbas and Abdelsamea [18], Karnkawinpong and Limpiyakorn [19]J. and Liu et al. [20].

3. Dataset Description

For our research we have utilized, two public datasets namely Shenzhen and Montgomery CXR Datasets, provided by the National Institute of Health (NIH)[21], United States have been used in the research. The Montgomery dataset was collected by the health department of the Montgomery County in Maryland, USA. The dataset has 138 labelled X-rays images with frontal view of the chest of which 80 images are CXRs of lungs with no disease, and 58 images shows lungs affected by tuberculosis.TheShenzen datasets source is the Guandong Hospital in Shenzhen. A total of 662 front view CXRs are a part of this data set of which 336 images are affected by TB, and 326 are disease free. In our experiment we use Shenzhen dataset for training and Montgomery dataset for testing and validation.

4. Data Pre-processing

Image pre-processing refers to the techniques and operations employed to our dataset in hand to enhance some features or to remove or supress some distortions, which might affect the outcome of the learning model. However image pre-processing does not increase the information contained in the image. In our research the following are the pre-processing techniques that have been employed.Contrast Enhancement, Augmentationand Resizing.

If the images have any border or black band around them we crop it and contrast improvement of the image is done using the using CLAHE[22] - Contrast Limited Adaptive Histogram Equalization Algorithm, Figure 4.1 depicts a sample CXR image before and after performing contrast enhancement.To improve the generalization and performance of the model, we have augmented the datasets in such a way that the resulting X-Rays are not distorted. The augmentation techniques employed are Rotations, horizontal flipping and perspective transformation.Figure 4.2 depicts all the augmentation process applied on to a single CXR from the dataset used.

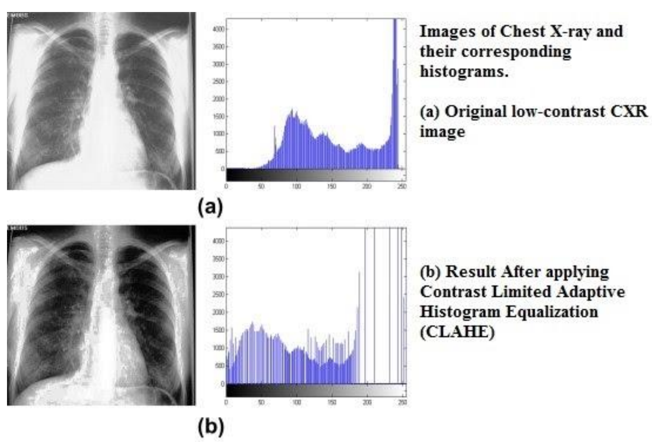

Fig 4.1. CXR Before and After Applying Contrast Enhancement

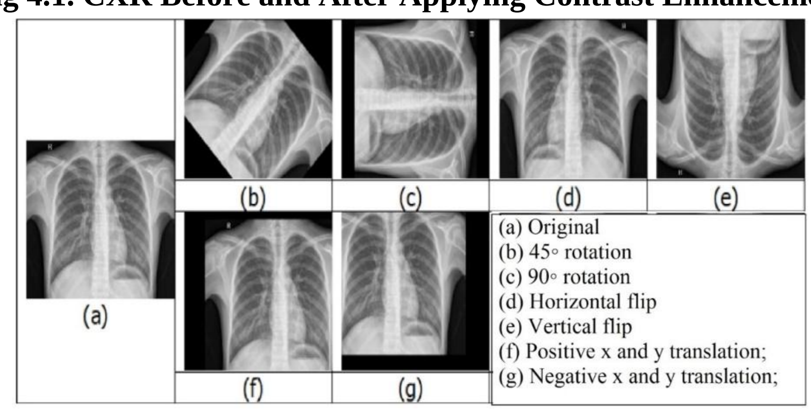

Fig 4.2 - A Sample CXR After the Augmentation Process

5. Method

The term "Freezing a Layer" in CNN means that the weights of that particular layer cannot be modified any further. For example if we take in to considerations a CNN model that has 2 layers,and if we assume that the first layer is frozen and the second layer not frozen and we run 50 epochs we will be performing exactly the same computation through the first layer for all of the 50 epochs, this means that for every epoch the inputs to the first layer are the same, the weight's in the first layer are the same and the outputs from the first layer are the same (images * weights + bias). Freezing - is a way of controlling how the weights are changed for the layers in a CNN. In this technique we will train the CNN faster by progressively freezing the hidden layers the learning rate governs thechange on the weights in a layer.

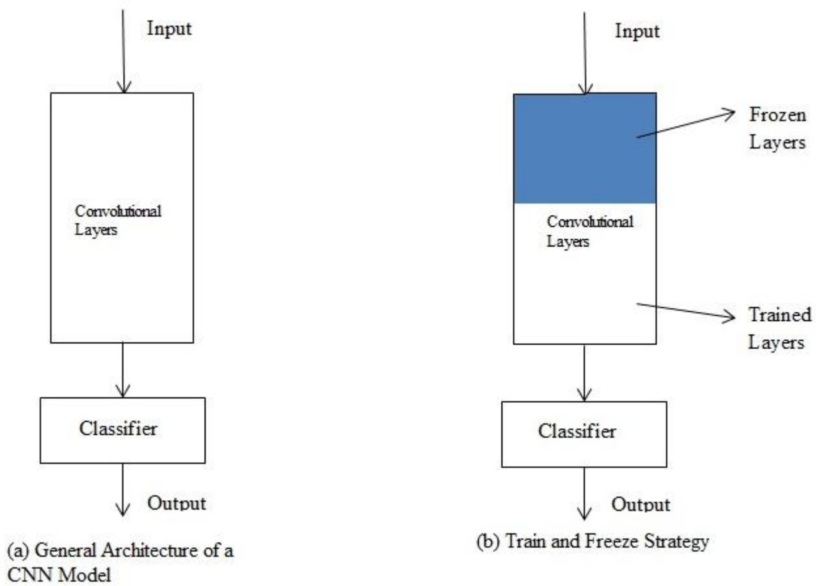

Fig .5.1 - Transfer Learning through Freeze Approach

The Train and Freeze approach is very useful when the available trained model has a lot more labelled data than the model at hand. The goal of the method is to Use ImageNet[13] weights for transfer learning[14]. The pre-trained models used for this purpose are VGG-16[8], VGG-19[8], ResNet50[6], DenseNet[12] and InceptionNet[5]. Parameters for these models such the training and validation splits, rate of learning, early stopping are kept uniform for all the models considered. The models are initialized with ImageNet weights and trained for 100 epochs. The pre trained model that gave the best classification result using the ImageNet weights is selected for performing the second half of the experiment.It was observed that pre-trained models that used skip connections, like ResNet and DenseNet121, outperformed the VGG-16 , VGG-19 which do not have skip connections. It was also observed that ResNet50 and DenseNet121 gave the best results. The performance of all the pre-trained models used has been tabulated in Table 4.7 . For the second part of the experiment DenseNet121[11]the results obtained it can be inferred that

DenseNet and Inception ResNet V2 exhibit similar AUC values for both the data sets under consideration. DenseNet was chosen as the pre-trained model for the next stage of the study as it is found to be superior to all the other models under consideration in terms of the number of parameters. It uses thrice the lesser number of parameters than all the other models under consideration. Figure 5.2 schematically shows the steps involved in this approach.

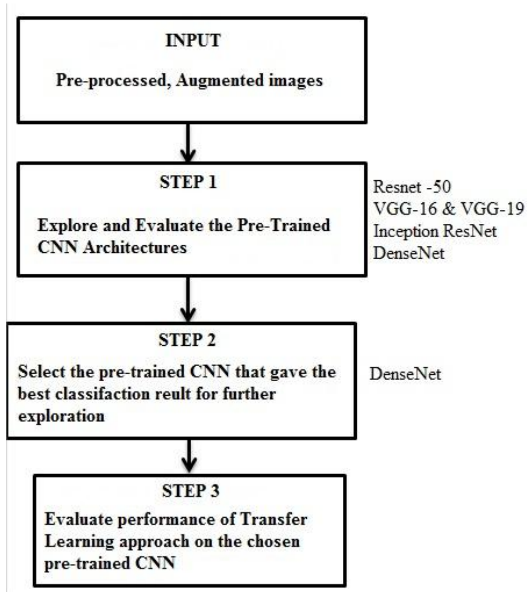

Figure 5.2 – Identifying the Best Pretrained Model Using Transfer Learning Approach

In the second stage of our experiment after benchmarking DenseNet101 as the pre-trained model of our choice we also explore how the number of convolutional blocks before the fully connected layer affects the output of the model. The convolution block is responsible for extracting the features and the fully connected layer performs the prediction based on the extracted features. Two fully connected dense layers are connected to the convolution blocks and the result is calculated bydirectly by taking the average of the final convolution layersby employing the formulae given by Equation (5.1)

$$\mathrm{Res}_{ab} = \sum_{n=1}^{d} \left(\frac{f_{a,b,c}}{d} \; \forall\, a \in A, b \in B \right) \quad (5.1)$$

Where: d = Count of feature maps, $f_{a,b,c}$= Value at position a,b,c of a feature map ,
A = function height and B= function width we set the values as A=1 and B=1.

On juxtaposing these values, we can observer the elements are susceptible to over-fitting and which elements are ideally suited for our classification.

Table 4.7– Performance of Pre-trained Models with ImageNet Weights

Model Used	**Weights**	**Shenzhen AUC**	**Montgomery AUC**
Resnet-50	ImageNet	.99	.70
VGG-16		.50	.50

VGG-19		.50	.50
Inception ResNet V2		.99	.80
Dense Net		.99	.80

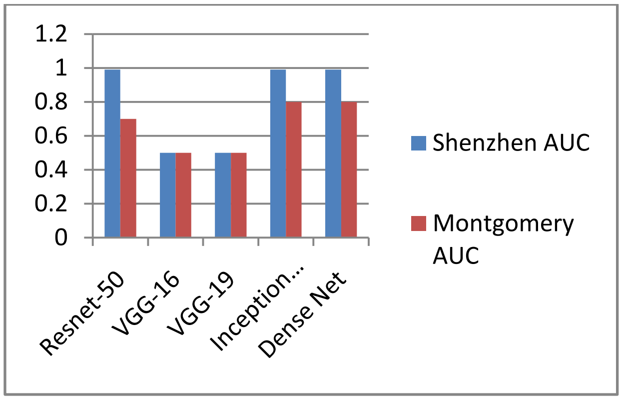

Fig 4.14 - Performance of Pre-Trained CNN's with ImageNet Weights

6. Results and Discussion

After benchmarking DenseNet as the eminent model amongst the other chosen models, we examine how well the benchmarked model performs with the weight on which it has been pretrained, that is: ImageNet weights. Further we examine if the features the model has learnt on the ImageNet dataset is applicable for our problem by unfreezing the layers and checkingforgrowth or decline in the models performance.The layers that were frozen and the corresponding classification performance has been summarized in the Table 6.1

Layers	Weight used for Initialization	Shenzhen AUC	Montgomery AUC
Freeze_all	ImageNet	.65	.54
Unfreeze_5		.65	.70
2 FCN +Freeze_all		.70	.69
2 FCN + Unfreeze_10		.80	.72
2 FCN + Unfreeze all		.99	.74
Global Average Pooling		.99	.82

Table 6.1- Performance of DenseNet Model

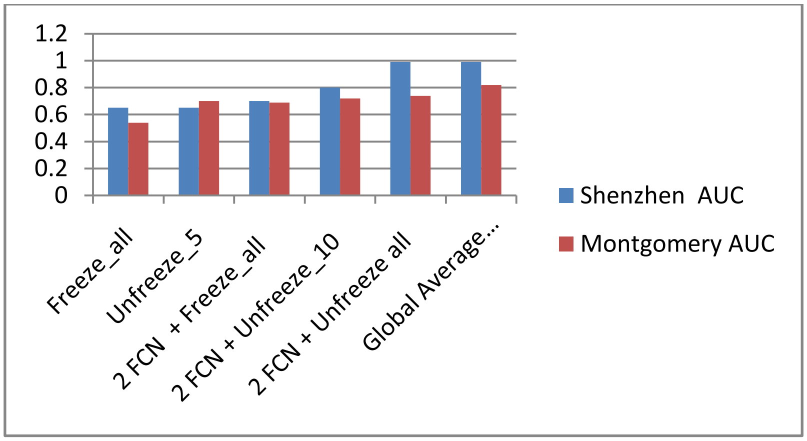

Figure 6.1 - Performance of DenseNet with Various Frozen Layers

From Table 6.1 and Figure 6.1, it can be observed that as more layers are unfrozen the performance of the model steadily increases.It can be inferred that to improve its performance the model has to learn new sets of features.A known issue with the fully connected layer is that this layer tends to overfit and rarely extends itself for generalization. We observed this with our models performance, the output of the DenseNet model when we use the averaging function is much superior than the results obtained with the fully connected layer.Thus we can infer that the ImageNet weights initialized pre-trained CNN's are non-practical for our classification task.

7. Conclusion

In this paper we have proposed a new strategy for identifying Tuberculosis in CXR by exploring transfer learning from pre-trained models through fine-tuning. We selected some of the best performing pre-trained models of ImageNet and evaluated them as classifiers over tuberculosis X-Ray dataset the best performing pre-trained model for our problem was identified as DenseNet. We experimented with DenseNet by examining if the features acquired from the ImageNet dataset is applicable for our classification by unfreezing the layers and looking for growthordecline in performance. We identified thatImageNet weights are insufficient for our problem at hand and the usage of appropriate data for pretraining is important and makes the entire process more efficient. For future works, it would be interesting to conduct a more broad investigation in identifying optimal non-architectural hyper-parameter values. An improved hyperparameter searching techniques such as grid search and random search might be able to discover moreideal configuration as opposed to trial-and-error approach we use in this research.

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