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Tuberculosis diagnosis using Deep Learning

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Abstract - *Tuberculosis (TB) is an airborne infectious disease and a major health threat that is deleterious in most parts of the world. Most of the diagnostic methods are time-consuming as well as unreliable and they were all mostly developed in the last century. Chest radiography is used as the most common method for screening TB in a large population. The success of this method depends solely on the experience and interpretation skills of the radiologist. Convolutional neural networks (CNN) is a deep learning strategy that has gained attention and popularity due to its ability to learn mid-level as well as high-level image representations. In this work, several CNN models such as InceptionV3, VGG19, ResNet50, and Xception were used, which classifies the chest radiographs into TB positive and TB negative classes. This paper offers a comparative study on the various deep learning techniques that can process chest x-rays and are capable of TB detection. The performance of the system is measured on a publicly available dataset: Tuberculosis (TB) Chest X-ray Database. The proposed CNN models trained for TB detection achieve accuracy of more than 80%, with the highest percent accuracy being at 98%.*

Key Words: **Tuberculosis, CNN, InceptionV3, VGG19, ResNet50, Xception, Deep Learning, Chest X-rays.**

1. INTRODUCTION

Tuberculosis (TB) is a chronic infectious disease, that most often affects the lungs, caused by Mycobacterium tuberculosis. It is an airborne disease that spreads from person to person, and about one-third of the world's population has its latent form, which means they have been infected by TB but cannot transmit it. According to World Health Organization (WHO), TB is one of the top 10 causes of death worldwide, surpassing HIV1 and Cirrhosis of the liver. Globally, an estimated 10 million people fell ill in 2019, a number that has been declining sporadically in recent years. There were an estimated 12 lakh TB deaths among HIV-negative people in 2019 and an additional 2 lakh deaths among HIV-positive people[1]. Adults accounted for 88% and youngsters for 12% of individuals with TB. The WHO regions of South-East Asia (44%), Africa (25%), and the Western Pacific (18%) had the foremost people with TB. Eight countries accounted for two-thirds of the global total: India (26%), Indonesia (8.5%), China (8.4%), the Philippines (6%), Pakistan (5.7%), Nigeria (4.4%), Bangladesh (3.6%) and South Africa (3.6%)[2].

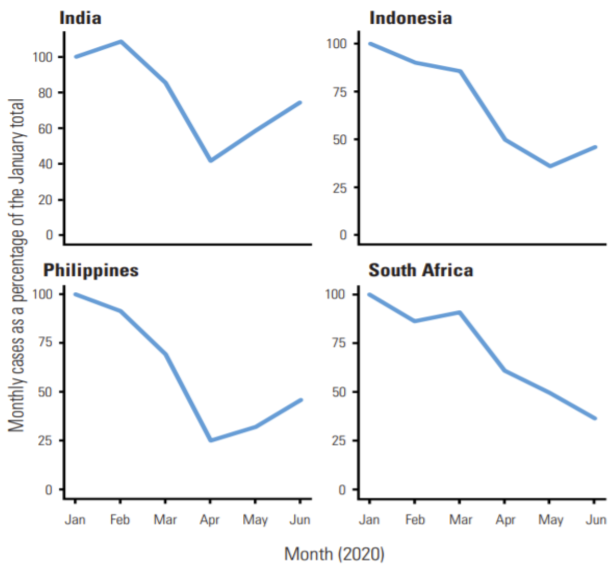

Fig-1: Trends in monthly notifications of people diagnosed with TB in four high TB burden countries, January–June 2020[2]

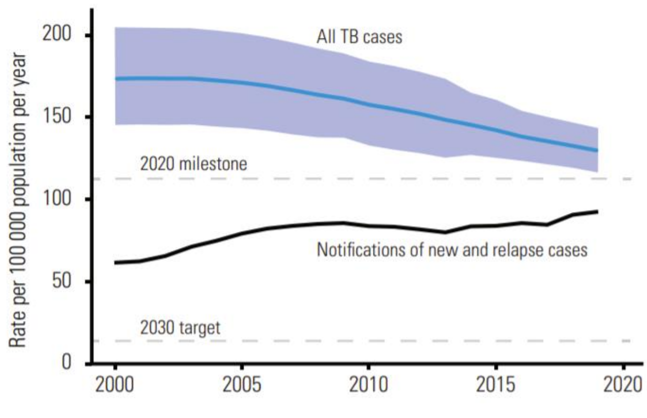

Fig-2: Global trend in the estimated TB incidence rate (blue), 2000–2019[2]

The TB incidence rate is depleting worldwide but not so fast enough to reach the speculated milestone of putting an end to TB around the globe. Worldwide, the cumulative pruning from 2015 to 2019 was 9%, including a reduction of 2.3% between 2018 and 2019.

2. RELATED WORK

The development of deep learning with neural networks and screening systems has made several breakthroughs in the field of science due to the emergence of digital chest radiography and the possibility of digital image processing. In the past few years, several revolutionary papers have been published on deep learning in CXRs, despite the need of more research in this field to meet the practical performance requirements.

[3] Proposed an improved methodology for TB detection through CXR images by deep CNN features. The proposed method gave rise to significant improvement in results. The Ensemble technique employed here worked better than the individual classifiers. The results showed that the proposed methodology can be successfully deployed as a mass screening tool for CXR based TB diagnosis.

[4] Proposed a transfer learning approach with deep Convolutional Neural Networks for the detection of tuberculosis from chest X-rays. ChexNet model proposed here outperforms other CNN models for the datasets. The classification accuracy, precision and recall for the detection of TB were found to be 97.07%, 97.34%, and 97.07%.

[5] Proposed models such as DenseNet-169, MobileNet, Xception and Inception-V3 to compare the results of CXR based TB detection. DenseNet169 performed best among the four and got 91.6% validation accuracy, 92% precision, 92% recall, 92% F1-score and AUC score of 0.915.

[6] Compared the performance of five deep learning models for improving the accuracy in TB detection from CXR. They have observed that AlexNet is notably better than VGG16, VGG19, Xception and ResNet50 models. The accuracy percent acquired were 84.3% for AlexNet, 81.4% for VGG16, 77.9% for VGG19, 73.2% for Xception and 81.7% for ResNet50.

[7] Proposed multiple deep CNN models (VGG16, VGG19, Inception V3, ResNet34, ResNet50, and ResNet101) for TB diagnosis from CXR. A linear average–based ensemble model composed of those improved CNN architectures was implemented and applied to improve the overall performance. The accuracy and f1 score obtained for each model were 91.15% and 87.9% for VGG16, 90.86% and 87.8% for VGG19, 91.49% and 88.7% for Inceptionv3, 91.40% and 88.7% for ResNet34, 90.96% and 87.7% for ResNet50, 90.97% and 87.6% for ResNet101, 92.07% and 89.1% for Ensemble.

3. DATASET

The dataset used here are publicly available chest radiographs or X-rays, made by a team of researchers from Qatar University, Doha, Qatar, and the University of Dhaka, Bangladesh along with their collaborators from Malaysia in collaboration with medical doctors from Hamad Medical Corporation and Bangladesh Datasets contain both normal and abnormal chest radiographs with manifestations of TB. There are 700 TB images, and 3500 normal images in the dataset. [8]

4. DEEP LEARNING

Deep learning is often subsumed as a part of machine learning, which essentially is a neural network with three or more layers. These neural networks try to simulate the behaviour of the human brain, thus allowing it to learn from large amounts of data. While a neural network with a single layer can still make approximate predictions, additional hidden layers can help to optimize the accuracy.

Deep learning drives many AI applications and services that improve automation, thus performing analytical and physical tasks without any means of human intervention. Deep learning technology lies behind everyday products and services as well as technologies about to rise in the near future.

4.1 Convolutional Neural Networks

Neural Networks are comprised of node layers, containing an input layer, one or more hidden layers, and an output layer. Each node connects to a different and has an associated weight and threshold. If the output of a node is above the required threshold value, then that node is activated, sending data to subsequent layer of the network. Otherwise, no data is passed along to the subsequent layer of the network.

Convolutional Neural Networks (CNNs) are generally utilized for classification and computer vision tasks. Before CNNs, several time-consuming feature extraction methods were used to identify objects in images. However, CNNs now provide a more viable approach to image classification and object recognition tasks, leveraging principles from linear algebra, to identify patterns within an image. That said, they can be computationally demanding too, like needing GPUs to train models.

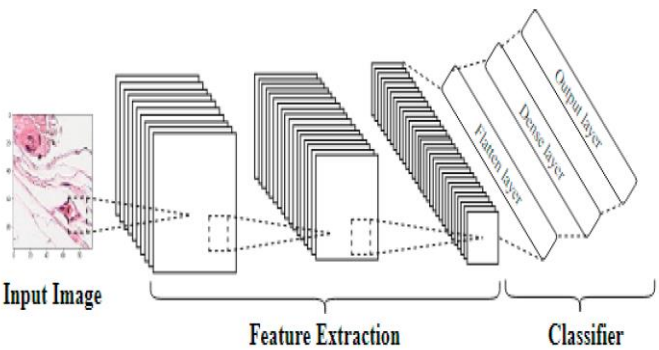

Fig-3: Convolutional Neural Networks [9]

5. MODELS

5.1 InceptionV3

Inception v3 is a widely acclaimed image processing model that has gained accuracy greater than 78.1% on the ImageNet dataset. The model is the apogee of many ideas developed by multiple researchers over the last few decades.

This model is made up of symmetric and asymmetric building blocks, including convolutions, average pooling, max pooling, concats, dropouts, and fully connected layers. Batchnorm is used extensively throughout the model and is applied to activation inputs. Loss is often computed with Softmax.

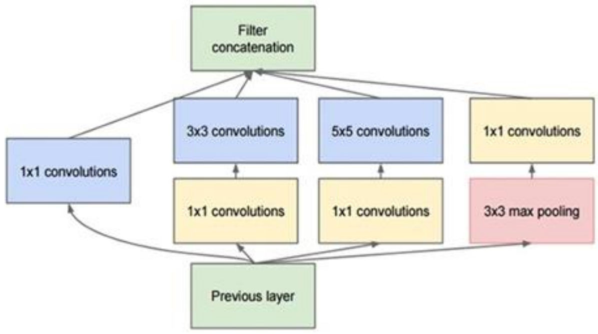

Fig-4: InceptionV3 architecture [10]

InceptionV3	
Trainable params	21,768,352
Non-trainable params	34,432
Total params	21,802,784

Fig-5: InceptionV3 parameters

InceptionV3			
	Precision	Recall	F1 Score
0	1.0	0.93	0.97
1	0.75	1.00	0.86
Accuracy			0.95
Macro avg	0.88	0.97	0.91
Weighted avg	0.96	0.95	0.95

Fig-6: InceptionV3 model evaluation

The above figure depicts the model performance of InceptionV3, which has attained an accuracy of 95%.

5.2 VGG19

VGG19 is subsumed as a variant of VGG model which consists of 19 layers (16 convolution layers, 3 fully connected layer, 5 MaxPool layers and 1 SoftMax layer). There are few other types of VGG models like VGG11, VGG16. VGG19 has 19.6 billion FLOPs. It uses some ideas from its predecessors and augments on them and uses deep Convolutional neural layers to improve accuracy.

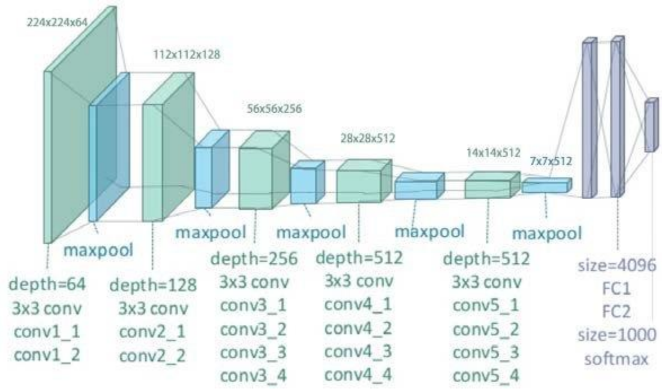

Fig-7: VGG19 architecture [11]

VGG-19	
Trainable params	143,668,241
Non-trainable params	0
Total params	143,668,241

Fig-8: VGG19 parameters

VGG-19			
	Precision	Recall	F1 Score
	0.83	1.00	0.91
Accuracy			0.83
Macro avg	0.42	0.50	0.45
Weighted avg	0.69	0.83	0.76

Fig-9: VGG19 model evaluation

The above figure depicts the model performance of VGG19, which has attained an accuracy of 83%.

5.3 ResNet50

A residual neural network (ResNet) builds on constructs known from pyramidal cells in the cerebral cortex. Residual neural networks do this by employing skip connections or shortcuts to jump over some subsequent layers. Standard ResNet models are executed with double or triple-layer skips that contain nonlinearities and batch normalization in between.

ResNet50 is subsumed as a variant of ResNet model which consists of 48 Convolution layers along with 1 MaxPool and 1 Average Pool layer. It has 3.8 x 10^9 Floating points operations. The main novelty of ResNet is the skip connection.

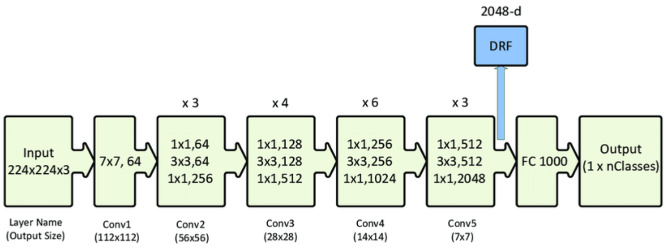

Fig-10: ResNet50 architecture [12]

ResNet50	
Trainable params	4,098
Non-trainable params	23,587,712
Total params	23,591,810

Fig-11: ResNet50 parameters

ResNet50			
	Precision	Recall	F1 Score
0	0.98	1.0	0.99
1	0.98	0.89	0.94
Accuracy			0.98
Macro avg	0.98	0.95	0.96
Weighted avg	0.98	0.98	0.98

Fig-12: ResNet50 model evaluation

The above figure depicts the model performance of ResNet50, which has attained an accuracy of 98%.

5.4 Xception

The Xception architecture owns 36 convolutional layers constituting the feature extraction base of the network. The 36 convolutional layers are structured into 14 modules, all of which have linear residual connections around them, except for the initial and terminal modules.

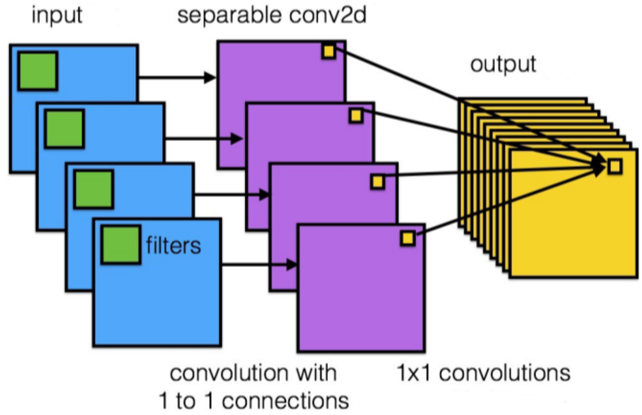

Fig-13: Xception architecture

Xception	
Trainable params	21,364,049
Non-trainable params	54,528
Total params	21,419,049

Fig-14: Xception parameters

Xception			
	Precision	Recall	F1 Score
0	0.99	0.99	0.99
1	0.96	0.94	0.95
Accuracy			0.98
Macro avg	0.97	0.96	0.97
Weighted avg	0.98	0.98	0.98

Fig-15: Xception model evaluation

The above figure depicts the model performance of Xception, which has attained an accuracy of 98%.

6. DISCUSSION & CONCLUSION

In this work we have worked with a few Convolutional Neural Network (CNN) models for the detection of Tuberculosis from chest X-rays. The developed system distinguishes positive and negative TB from the dataset provided. Though models like InceptionV3, ResNet50 and Xception produced almost the same accuracy, ResNet50 outperformed others in terms of time consumption, loss rate and an accuracy slightly better (98%). We have used 3360 images for training and the remaining for validation and testing, for each model.

The usage of augmentation methods to increase the dataset is not a good idea in the case of medical data, as the model learns some specious patterns which cause the decrease in the accuracy of the model. The method of deep learning, in which a model pre trained on some dataset is used on another dataset, is useful if the dataset on which it is going to be used is already known to the model. The accuracy of the model can be further improved by increasing the chest X-rays dataset, with a greater number of images, thus more features will be learned by the model.

The Conventional diagnosis of Tuberculosis still requires more involvement and the presence of medical experts and specialists, to build a good and reliable Tuberculosis Detection model. And it is also particularly important to collect and train as much data as possible.

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