CLASSIFICATION OF CHEST DISEASES FROM X-RAY ON CHEXPERT DATASET

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It is dedicated to my inspiring parents for their love, endless support, encouragement and sacrifices.

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ABSTRACT

This work proposes a method to classify tuberculosis (TB) disease in a chest radiograph using convolutional neural network algorithms (CNN). The main contribution of this work is to detect and classify 'TB' disease in addition to other 5 different diseases. This is achieved by using a transfer learning technique that utilizes a pre-trained 'CNN' network to classify the 'TB' disease. A comprehensive verification using TensorFlow is carried out to train and validate the proposed technique. This work aimed to use different pre-trained models on the CheXpert dataset and compare the area under the curve 'AUC' between the 'CNN' models. From the simulation work, it was found that it can be possible to classify the 'TB' in addition to the other 5 diseases without having a high reduction in the accuracy of classifying the 5 diseases. The results confirm that transfer learning technique is superior to the other methods, which exhibit less time for training and validating the datasets, and have good performance. This work achieved a new state of the art for classifying 3 different diseases (Atelectasis, Edema, and Tuberculosis) with 'AUC' 0.912, 0.945 and 0.954 respectively. Also, this work achieved second-best performance for classifying Pleural Effusion and Consolidation diseases with 'AUC' 0.928 and 0.917 respectively. The method proposed in this work can be used for all types of classification diseases in chest radiograph because it can be easily implemented by using pre-trained networks.

ABSTRAK

Kerja ini mencadangkan satu kaedah untuk mengklasifikasikan penyakit tuberkulosis (TB) dalam radiografi dada menggunakan algoritma perlingkaran rangkaian neural. Sumbangan utama kerja ini adalah untuk mengesan dan mengklasifikasikan penyakit 'TB' sebagai tambahan kepada lima jenis penyakit lain yang berbeza. Perkara ini dapat dicapai dengan menggunakan teknik pembelajaran pemindahan yang menggunakan perlingkaran rangkaian neural yang pra-terlatih untuk mengklasifikasikan penyakit 'TB'. Pengesahan yang menyeluruh menggunakan 'TensorFlow' telah dijalankan untuk melatih dan mengesahkan teknik yang dicadangkan dalam kajian ini. Kerja ini bertujuan untuk menggunakan model pra-terlatih yang berbeza daripada set data 'CheXpert' dan membandingkan 'AUC' antara model-model perlingkaran rangkaian neural. Hasil daripada simulasi yang dijalankan didapati bahawa pengklasifikasian penyakit 'TB' sebagai tambahan kepada lima penyakit yang lain dapat dilaksanakan tanpa pengurangan yang tinggi dalam ketepatan dalam mengklasifikasikan lima penyakit. Keputusan daripada simulasi yang dijalankan mengesahkan bahawa teknik pembelajaran pemindahan adalah lebih baik daripada kaedah-kaedah yang lain, berikutan masa yang pendek diperlukan untuk latihan dan mengesahkan set data serta mempunyai persembahan yang baik. Kerja ini mencapai keadaan seni yang baru untuk mengklasifikasikan 3 jenis penyakit yang berbeza [Atelectasis, Edema dan Tuberkulosis] dengan masing-masing mempunyai AUC [0.912, 0.945 dan 0.954]. Selain itu, kerja ini berhasil mencapai tempat kedua terbaik dalam mengklasifikasikan penyakit-penyakit 'Pleural Effusion and Consolidation' yang masing-masing mempunyai 'AUC' [0.928 dan 0.917]. Kaedah yang dicadangkan dalam kerja ini boleh digunakan untuk semua jenis penyakit klasifikasi dalam radiografi dada kerana kaedah ini mudah dilaksanakan dengan menggunakan rangkaian pra-terlatih.

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LIST OF ABBREVIATIONS

AG-CNN	-	Attention Guided Convolution Neural Network
AI	-	Artificial Intelligence
AUC	-	Area Under the Curve
CAD	-	Computer Aided Diagnosis
CNN	-	Convolutional Neural Network
CPU	-	Central Processing Unit
CXR	-	Chest X-Ray
DL	-	Deep Learning
FN	-	False Negative
FP	-	False Positive
GAN	-	Generative Adversarial Network
GPU	-	Graphics Processing Unit
HLL	-	High Level Language
lr	-	Learning rate
LSTM	-	Long Short-Term Memory
NAN	-	Not A Number
NIH	-	National Institutes of Health
PWE	-	Pair Wise Error
ReLU	-	Rectified Linear Unit
RGB	-	Red, Green and Blue
SVM	-	Support Victor Machine
TB	-	Tuberculosis
TL	-	Transfer Learning
TN	-	True Negative
TP	-	Ture Positive

CHAPTER 1

INTRODUCTION

Chapter one has five sections. Section 1.1 shows the project background. In section 1.2 problem statement is clearly justified. Section 1.3 shows the objectives for this work. The next section shows the framework for this project. Finally, planning of this project report is illustrated in section 1.5.

1.1 Project Background

Tuberculosis (TB) is an infectious disease caused by the bacillus Mycobacterium tuberculosis. According to the World Health Organization, tuberculosis (together with HIV/AIDS) is the deadliest infectious disease in the world. In 2015, the World Health Organization estimated that around 9.6 million people were infected with TB, leading in 1.5 million deaths (1.1 million Aids-negative and 0.4 million Aids-positive) [1]. The percentage of infected individuals increased dramatically by 2016: 10.4 million confirmed cases of the illness and 1.8 million deaths were recorded. (1.4 million Aids-negative and 0.4 million Aids-positive) [2]. Most of these deaths might have been avoided if the disease was identified in earlier phases.

Chest radiographs seem to be the most popular radiological examinations. They are important for the management of different pathologies related to high death rates and present a large variety of potential knowledge, many of which is overt. The most popular studies in chest x-rays involve lung infects, catheters and abnormalities of the size or contour of the heart, thus most study in computer-aided detection and diagnosis of chest x-rays has concentrated on these pathologies [3]. Automated thoracic radiography interpretation at the stage of performing clinicians can provide significant benefits in several clinical settings, from enhanced workflow prioritization and clinical decision-making support to huge-scale examination and global population medical programs.

In past years, deep learning strategies have accomplished excellent results in a wide range of machine learning activities [4]. Convolutional Neural Networks (CNN) have confirmed to be particularly strong for image classification tasks, and have been successfully applied in a variety of areas, such as galaxy morphology estimation [5], Advancement of photo-guided autonomous cars [6], face detection [7][8], huge-scale video classification [9] and many others [10][11][12]. There are already several Computer Aided Diagnostic (CAD) systems that use CNNs to detect diseases [13][14][15][16][17][18][19][20]. However, its implementation of tuberculosis (TB) detection stays limited.

1.2 Problem Statement

In the United States. the percentage of pathologists as the number of the medical workforce is declining [21], and the geographical distribution of pathologists favors wider, more urban counties [22]. Delays and backlogs in the timely interpretation of radiography have shown an evidently decreased quality of healthcare in this kind of massive health institutions as the United Kingdom. The National Health Service [23] and the United States Department for Veterans Affairs [24]. The scenario is much worse in resource-poor areas where radiological facilities are pretty scarce. As of 2015, only 11 radiologists have served 12 million Rwandans [25], whereas the entire nation of Liberia, with a population of 4 million, has only two performing radiologists [26]. Precise automated radiographic analysis has the potential to increase the efficiency of the pathologist workflow and widen expert knowledge to underserved countries.

It has been recorded that there is a proportional lack of expertise in the assessment of radiology in several common locations of TB, which may minimize screening effectiveness and work-up initiatives [27][28]. Therefore, there has been an interest in the use of computer-aided diagnosis for the detection of pulmonary TB at chest radiography, with various strategies presented [27][29][30]. These days, there are several extremely accurate diagnostic techniques depending on molecular analysis and bacteriological culture, but unfortunately, most of them cost prohibitively for mass adoption in developing countries that are most affected by the disease. The lowest cost and most common diagnostic methods, such as sputum smear microscopy, are recorded to have sensitivity problems [31]. Another common diagnostic method uses frontal chest radiographic images, but unfortunately, this technique is restricted by the need for skilled staff to independently monitor every radiography that is not present in developing countries. If an automated technique was discovered capable of identifying the disease, it could support current diagnostic strategies and be used as a large scale detection tool to screen large populations that could not be managed manually [32], thereby significantly reducing costs and potentially saving many lives.

Hence, a focus to research and development of a novel approach is important to tackle chest X-ray images with various chest diseases such as Tuberculosis (TB), Lung infiltrates, catheters, Pneumothorax, Pleural Effusion, Edema, and Cardiomegaly. Also, improve classification accuracy. This project proposes an enhanced deep learning Convolutional Neural Network (CNN) model with the transfer learning technique.

1.3 Objectives

Two primary goals characterized for this work

(a) To do classification on CheXpert dataset for the different pathologies using different CNN models by applying transfer learning technique.

(b) To do classification for the new combined dataset that contains TB disease.

1.4 Scope of work

The framework is shown in Table 1.1

Table 1.1 Scope of work

SCOPE	DETAILS
Platform	TensorFlow 2.0 – Open source machine learning library. PyTorch 1.3– Open source machine learning library.
Tool	Python 3.7.2 – Programming High level language
Area	Chest radiographs classification.
Focus	Classification accuracy on 5 diseases in radiology reports. In addition to classify TB disease.
Dataset	CheXpert dataset [33], which consist of 224,316 chest X-ray images of 65,240 patients. (frontal and lateral views). Two datasets [34], that contains the TB disease (frontal radiographs): 1- Guangdong Medical College, Shenzhen, China dataset, which consist of: 662 chest radiographs. 2- Montgomery County, MD, USA dataset, which consist of: 138 chest radiographs.
Model	DenseNet [35], GoogleNet [36], AlexNet [37], VGGNet [38], ResNet [39] and SequeezeNet [40]

1.5 Project Report Outline

There are five chapters in this work:

Chapter 1 is the introduction of this work which contains: project background, problem statement, objectives, the scope of work and finally the project planning.

Chapter 2 is the literature review of this work. The history of deep learning, Architecture of Convolutional Neural Network (CNN), transfer learning technique and related works similar to this project are all shown in chapter 2.

Chapter 3 is the methodology of this work. shows how to use the TensorFlow platform to implement CNN classification. The architecture of the proposed model, the selection of the pre-trained network, transfer learning technique are all clearly discussed. Finally, preparing the datasets for this work is plainly shown in chapter 3.

Chapter 4 is the results and benchmarking of this work. The results of the application of transfer learning are discussed. The AUC of the different CNN pre-trained models is shown. Training and validation of chest X-ray datasets on the pre-trained models are shown.

Chapter 5 Conclusion and future work attached to this work are clearly shown.

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