CHEST INFECTION CLASSIFICATION FROM X-RAY IMAGES USING ENHANCED MULTISOURCE TRANSFER LEARNING WITH VOTING SYSTEM

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Specially dedicated to my beloved family, lecturers and friends for guidance, encouragement and inspiration throughout my journey of education.

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ABSTRACT

Chest infection is a major health threat in most regions of the world. It is claimed to be one of the top causes of postoperative death after fragility hip fractures, according to a study presented in 2011. With the invention of deep learning in machine learning, implementation in Computer Aided Diagnosis system which utilizes deep neural networks for learning, classification, generation and even clustering has allowed X-ray image classification to be more accurate. The improvement in medical image classification using transfer learning is further studied. In this thesis, a novel deep neural network model which is composed of two Convolutional Neural Networks (CNNs) with different depth of weight layers, where the prediction probabilities for all CNNs are fused to the voting system for chest X-ray image classification is proposed and presented. The performance and accuracy of several existing deep learning model are investigated and compared to the proposed model. The outcome of this work, we successfully classified chest infection in chest X-ray images using the proposed model with overall accuracy of 83.69%.

ABSTRAK

Jangkitan dada adalah ancaman kesihatan utama di kebanyakan rantau di dunia. Ia dikatakan sebagai salah satu penyebab utama kematian selepas operasi keretakan pinggul kerapuhan, menurut kajian yang dikemukakan pada tahun 2011. Dengan penciptaan pembelajaran mendalam dalam pembelajaran mesin, pelaksanaan dalam Diagnosis Bantuan Komputer (CAD) yang menggunakan rangkaian saraf dalam untuk pembelajaran, klasifikasi, generasi dan klustering telah membolehkan pengelasan imej X-ray menjadi lebih tepat. Peningkatan klasifikasi imej perubatan menggunakan pembelajaran pemindahan terus dikaji. Dalam tesis ini, model rangkaian neural mendalam yang terdiri daripada dua *Convolutional Neural Networks* (CNNs) dengan kedalaman lapisan berat yang berlainan, di mana kebarangkalian ramalan untuk semua CNNs bersatu dengan sistem pengundian untuk klasifikasi imej X-ray dada dicadangkan dan dibentangkan. Prestasi dan ketepatan beberapa model pembelajaran dalam yang sedia ada akan disiasat dan dibandingkan dengan model yang dicadangkan. Hasis kerja penyelidikan ini telah berjaya mengelaskan jangkitan dada dalam imej X-ray dada menggunakan model yang dicadangkan dengan ketepatan keseluruhan sebanyak 83.69%.

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LIST OF ABBREVIATION

AI	-	Artificial Intelligence
CAD	-	Computer Aided Diagnosis
CNN	-	Convolution Neural Network
DL	-	Deep Learning
FC	-	Fully Connected
FN	-	False Negative
FP	-	False Positive
ReLU	-	Rectified Linear Units
TL	-	Transfer Learning
TN	-	True Negative
TP	-	True Positive

LIST OF SYMBOLS

k	-	k^{th} Model
p	-	Probability
x	-	Input Image X
y	-	Prediction Class Label

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CHAPTER 1

INTRODUCTION

This chapter has five sections. Section 1.1 introduces the background of this project. Problem statement is justified in Section 1.2. Then the objectives for this project are clearly declared in Section 1.3. The following section discusses the scope of work for the project setup and implementation. Lastly, organization of this report is described in Section 1.5.

1.1 Project Background

Chest infection is a major health threat in most regions in the world. It is claimed to be one of the top causes of postoperative death after fragility hip fractures, according to a study presented by Alice Tsai at the 12th European Federation of National Associations of Orthopaedics and Traumatology (EFORT) Congress 2011 [1]. According to the Statistics on Causes of Death from the Department of Statistic Malaysia [2], Ischemic heart diseases was the principal cause of death in 2016 of 13.2 per cent, followed by pneumonia (12.5%), cerebrovascular diseases (6.9%), transport accidents (5.4%) and malignant neoplasm of trachea, bronchus & lung (2.2%). Most of the leading causes mentioned can be considered as chest infections and require chest X-ray examination at some stage of disease management which is normally done by visual examination by experienced radiologists. In fact, it is a difficult task even to the human observer to distinguish between various chest pathologies.

Automatically detection of abnormalities in lung from chest X-rays with high accuracy Computer Aided Diagnosis (CAD) system could greatly enhance real world diagnosis processes as it may assist radiologists in reading chest images or even replace human in chest pathology identification. Deep learning techniques, have recently been introduced for medical image analysis, with promising results in various applications like medical image segmentation and classification [3]. With the invention of deep learning in machine learning, implementation in CAD which utilizes deep neural networks for learning, classification, generation and even clustering has allowed X-ray image classification to be more accurate.

Deep learning has received a great interest and has been trending due to the rise of more powerful GPUs, sophisticated neural network algorithms modelled after the human brain, and access to the explosion of data from the internet. There is one saying, “The analogy to deep learning is that the rocket engine is the deep learning models while the fuel is the huge amounts of data we can feed to these algorithms.” These techniques are most effective when applied on large datasets for training. However in the medical field, such large datasets with correct label and pre-defined metadata are usually not available.

1.2 Problem Statement

Transfer Learning (TL) becomes an alternative for the case of small dataset. However, previous studies suggest that transfer learning is most effective when the sets are similar [4]. It is a challenge to classify grayscale X-ray image using pre-trained model with coloured and non-medical images causing features learnt is hardly transferable. Even though transfer learning has been the interest of research on the field of deep learning in medical image classification, any deep architecture methods for the specific task of pathology detection in chest radiographs are not aware [5].

Among the research on transfer learning in the field of medical chest X-ray image classification, the focus is more likely onto abnormal and normal class detection. Some of the researches focus on classifying chest X-ray image to multiple disease using deep learning. However, it comes to a limitation when the chest X-ray image is from a patient diagnosed with multiple chest diseases. On top of that, the accuracy of the prediction of possible diseases on chest X-ray image in CAD systems nowadays is not convincing.

Hence, a focus to research and develop a novel approach is important to tackle chest X-ray images with multiple chest diseases and improve classification accuracy. In this research project, an enhanced deep learning Convolutional Neural Network (CNN) model with multisource transfer learning and voting system is proposed.

1.3 Objectives

There are a three main objectives defined for this project, they are:

i) To automate preparation of the dataset in labeling and preprocessing to be used as input dataset to the model.

ii) To train and validate the performance of transfer learning pre-trained convolutional network to obtain high accuracy in classifying X-ray images into multiple chest infections.

iii) To develop an enhanced CNN model which applies multisource transfer learning and voting system methodology for multiple chest infection classification with improved accuracy.

1.4 Scope of Work

The scope of work for this research project is clearly presented in the Table 1.1.

Table 1.1: Scope of work

SCOPE	DETAILS
Platform	TensorFlow 1.7.0 – Open source machine learning library.
Tool	Python 3.5.2 – High level programming language.
Field	Chest X-ray Image classification
Focus	Transfer learning techniques and classification accuracy on 4 categories of chest infections (Pulmonary Atelectasis, Calcified Granulomatous disease, Cardiomegaly and Lung Hypoinflation)
Dataset	Chest X-ray images from National Library of Medicine https://openi.nlm.nih.gov/gridquery.php?q=&it=x,xg&sub=x (7468 images – including frontal and side view of human chest)
Model	VGGNet and Inception-ResNet

1.5 Project Report Outline

This thesis consists of five chapters. Chapter 1 is the introduction of this research project. Project background, problem statement, objectives, scope of work, and the project organization are discussed.

Chapter 2 is the literature review of this research project. The studies and research findings on deep learning, Convolutional Neural Network architectures, transfer learning, and related works on the existing research are presented in this chapter.

Chapter 3 is the research methodology of this project. The architecture of the proposed model which is composed of two CNNs with combined average weight on the output probabilities on each classes is presented. Proposed methodology is further discussed in detail on selected pre-trained networks, multisource transfer learning and voting system. Lastly, the dataset preparation for this project is clearly explained including the preparation of chest X-ray image dataset.

Chapter 4 is the result and discussion of this project. The results on the application of transfer learning are discussed. The accuracy of the model is shown. Training of chest X-ray dataset and validation result for individual CNN model is shown. Evaluation and accuracy of the proposed model on classifying chest diseases are clearly presented in this chapter.

Chapter 5 is the conclusion. Future works related to this project are discussed on this chapter.

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