

CLASSIFICATION OF COVID-19 AND OTHER LUNG DISEASES FROM
CHEST X-RAY IMAGES

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DEDICATION

This thesis is dedicated to all hardworking and kind fathers, like dear father of mine, who are full of love to their families and support their families during their whole life.

It is also dedicated to all mothers, like dear mother of mine, who never forget for a moment to take care of upbringing as well as educating of their children. The dear loyal mothers who support and encourage their children to try to be a useful and valuable person for the society and humanity.

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ABSTRACT

There are several lung diseases such as pneumonia, asthma, tuberculosis, and fibrosis. The most recently, coronavirus disease 2019 (COVID-19), is rapidly spreading and cause a pandemic with a many of victims. The standard test method for diagnosis of the disease, described by World Health Organization (WHO), is Real-time reverse transcription polymerase chain reaction (RT-PCR) which takes long from several hours to two days. In addition, considering some shortcoming of the testing by kit, such as limitation in number of kits, and probability to spread the virus during the test procedure depicts a necessary of presenting automatic diagnosis of COVID-19 from medical imaging such as chest X-ray to control this dangerous pandemic. This study aims to develop and test several different deep learning models using Convolutional Neural Network (CNN)-based models as well as vision transformer (ViT) in image classification to automatically diagnose COVID-19 and other kinds of lung diseases using chest X-Ray as input image. In this thesis, different CNN-based deep learning models are proposed. This CNN-based models can be trained to classify chest X-ray images into three classes of COVID-19, normal chest X-ray and other lung diseases. The different proposed models will be trained with three-class balanced dataset which consists of 3000 images, 1000 images for each class. Besides, the binary classification between two classes of COVID-19 and normal chest X-ray is proposed. In addition of using CNN, two different models are trained with three-class dataset. Nine different models and their results is proposed with a comparison of their results. A publicly available dataset to train and test the CNN model is used from Kaggle-COVID-19_Radiography_Dataset. From the experiments, the accuracy of VGG16 model is 93.44 % and ViT is 92.33 %.

ABSTRAK

Terdapat beberapa penyakit paru-paru seperti radang paru-paru, asma, batuk kering, dan fibrosis. Penyakit coronavirus 2019 (COVID-19) yang paling baru, merebak dengan cepat dan menyebabkan wabak dengan banyak mangsa. Kaedah ujian standard untuk diagnosis penyakit, yang dijelaskan oleh Pertubuhan Kesihatan Sedunia (WHO), adalah reaksi berantai polimerase transkripsi terbalik masa nyata (RT-PCR) yang memakan masa lama dari beberapa jam hingga beberapa hari. Di samping itu, mempertimbangkan beberapa kekurangan ujian oleh kit, seperti batasan jumlah kit, dan kebarangkalian menyebarkan virus semasa prosedur ujian, maka terdapat keperluan diagnosis automatik COVID-19 dari pengimejan perubatan seperti sinar-X dada untuk mengawal wabak berbahaya ini. Kajian ini bertujuan untuk mengembangkan dan menguji beberapa model pembelajaran dalam yang berbeza menggunakan model berdasarkan Rangkaian Neural Konvolusional (CNN) serta pengubah penglihatan (ViT) dalam klasifikasi gambar secara automatik mendiagnosis COVID-19 dan jenis penyakit paru-paru lain menggunakan sinar-X dada sebagai gambar input. Dalam tesis ini, model pembelajaran mendalam berasaskan CNN yang berbeza dicadangkan. Model berasaskan CNN ini dapat dilatih untuk mengklasifikasikan gambar sinar-X dada menjadi tiga kelas COVID-19, sinar-X dada normal dan penyakit paru-paru lain. Model yang dicadangkan berbeza akan dilatih dengan set data seimbang tiga kelas yang terdiri daripada 3000 gambar, 1000 gambar untuk setiap kelas. Selain itu, dicadangkan pengkelasan binari antara dua kelas COVID-19 dan sinar-X dada normal. Selain menggunakan CNN, dua model yang berbeza dilatih dengan set data tiga kelas. Sembilan model yang berbeza dan hasilnya dicadangkan dengan perbandingan hasilnya. Set data yang tersedia untuk umum untuk melatih dan menguji model CNN digunakan dari Kaggle- COVID-19_Radiography_Dataset. Dari eksperimen, ketepatan model VGG16 adalah 93.44% dan ViT adalah 92.33%.

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LIST OF ABBREVIATIONS

AI	-	Artificial Intelligence
ANN	-	Artificial Neural Network
CADx	-	Computer Aided Diagnosis
CADe	-	Computer Aided Detection
COVID	-	Coronavirus disease
CT	-	Computed tomography
DL	-	Deep Learning
GPU	-	Graphical Processing Unit
MRI	-	Magnetic Resonance Imaging
NN	-	Neural Network
ML	-	Machine Learning
ROC	-	Receiver Operating Characteristics curve
RT-PC	-	Real-time reverse transcription polymerase chain reaction
ROC	-	Receiver Operating Characteristics curve
SARS	-	Severe Acute Respiratory Syndrome
ViT	-	Vision Transformer
WHO	-	World Health Organization

- Because of parallel data processing in Vision Transformer, as theoretically is expected, ViT should be faster than pretrained VGG16 model. Comparing the time of training the 3-classes classification models, in experiences 8-A and 8-B of this project, with other pretrained models' training time reveals that in this 3-class application using ViT model 'Vit_base_patch16_224_in21k' in experience 8-B with 92.33 % accuracy in 14 minutes is more accurate and faster than model 'Vit_base_resnet50_224_in21k' and pretrained VGG16.

5.2 Future Work

Swin transformer is a hierarchical vision transformer using shifted windows. This hierarchical structure forms by starting from small-sized patches of the image and gradually merging the neighboring patches in deeper transformer layers. Partitioning an image with non-overlapping windows, which consist of fix number of patches, will have linear complexity of computation to image size during locally self-attention of these windows. Thus, Swin transformer can build hierarchical feature maps by merging image patches in deeper layers as well as linear complexity to input image size because of self-attention only within each local window.

The chest X-ray image consists of images of different tissues of the body protected by the chest. In addition, in some cases the shape of cables or other equipment of medical caring can be seen in a chest X-ray image. Consequently, it causes to decrease the accuracy of a model because they are considered as image's features of a class.

Shifting of the window partition between consecutive self-attention layers is the main design element of this approach. Next layer is formed by shifting the partitioning window and self-attention in this new window crosses the boundaries of previous window in previous layer.

In contrast, previous vision transformers produce feature map of a single low resolution and have quadratic computation complexity to input image due to computation of self-attention globally.

There is a valuable work in this field [6] in which the authors have shown that Swin Transformer achieves the state-of-the-art performance on COCO object

detection and ADE20K semantic segmentation, significantly surpassing previous best methods.

Similarly, Getting the benefit of the hierarchical vision transformer of Swin transformer can improved the ability of segmenting an image. It means, with less computational cost can focus on the specific sections by which can extract more dominant features of an input X-ray images related to a specific disease. There is the hope that Swin Transformer has strong performance on vision problems and it will encourage unified modeling of vision and language signals.

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