## University Name

## DOCTORAL THESIS

## Thesis Title

Author:
John Smith

 $Supervisor: \\ Dr. James Smith$ 

A thesis submitted in fulfillment of the requirements for the degree of Doctor of Philosophy

in the

Research Group Name Department or School Name

January 16, 2023

## Abstract

The Thesis Abstract is written here (and usually kept to just this page). The page is kept centered vertically so can expand into the blank space above the title too...

## Acknowledgements

The acknowledgments and the people to thank go here, don't forget to include your project advisor...  $\,$ 

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## Introduction

#### 1.1 Main Section 1

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## 3.2 Main Section 2

## Proposed Work

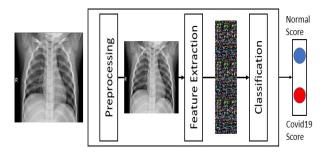


FIGURE 4.1: The phases of the proposed method.

## 4.1 The Proposed Method

In this section, a proposed method to detect COVID-19 disease from chest X-Ray images is presented. The proposed method exploits CNN model to classify the input chest X-Ray image to one of two categories; normal case or Covid-19 case. The proposed method consists of three phases: preprocessing, feature extraction, and classification. The proposed method phases are shown in Fig.4.1.

## 4.1.1 The Preprocessing Phase

The preprocessing phase is responsible for resizing and normalizing the input chest X-Ray images. The pre-processing phase is employed to maintain the numerical stability of the model and reduce the co-variance shift [1]. In addition, this phase leads the learning model of CNN model to reduce the required overhead to adapt to the different scales of different features of the input data. Reshaping size is determined empirically. The input chest X-Ray image is re-sized and then adapted and normalized to a normal distribution as follows:

$$Y := \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma_{\mathcal{B}}^2 + \epsilon}} \tag{4.1}$$

where  $\mu$  and  $\sigma$  is the mean and standard deviation of chest X-Ray image (X), respectively.

After re-sizing the input chest X-Ray image, the input image is normalized to have a zero mean and unit standard deviation. Then, the image can be scaled and shifted

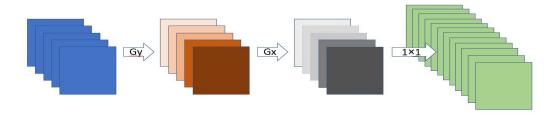


FIGURE 4.2: Separable convolution Gy and Gx have kernel size of  $M \times 1$  and  $1 \times M$ . The combination of these kernels is approximately a  $M \times M$  kernel and depth wise convolution are applied by a  $1 \times 1$  convolution. The output depth is padded with zeros to have the same spatial size of Gy, Gx. Gy, Gx are performed channel wise.

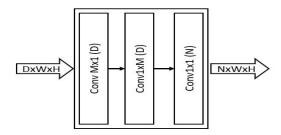


FIGURE 4.3: Separated Convolutional Layer

composed of three consecutive layers. The first Convolutional layer has a kernel size of  $(M \times 1)$  and D convolutional neuron. The second layer operates in the same way as the first layer but it has a kernel of size  $(1 \times M)$  and D convolutional neuron. The third layer is the convolutional layer with kernel of size  $(1 \times 1)$  and number of convolutional neuron is N.

with a normalization parameter which is determined and adapted by the training dataset during the training process according to the following equation:

$$Z := w_1 Y + w_2 \tag{4.2}$$

where  $w_1$  and  $w_2$  are a trainable parameter.

Unlike the normalization method presented in [2], the batch normalization process presented in this paper has z-score normalization parameter that is used in both training and validation phases.

#### 4.1.2 Feature Extraction and Classification

CNN models achieved an outstanding success in image recognition [3]. This phase is responsible for extracting spatial features from the normalized chest X-Ray image using a tailored CNN model. This phase is based on learning the CNN model by the input preprocessed chest X-Ray images. The design of the tailored CNN model is described as follows:

#### 1) Separable CNN kernels

Kernel separability[4] [5] is based on decomposing a 2D convolution kernel to linear combinations of two 1D vectors which leads to a large reduction in the total number of resulting parameters. For example, a 2D kernel of size  $9 \times 9$  has a total number of  $9^2 = 81$  trained parameters. Whereas in the case of separating this 2D kernel to linear

combinations of two 1D vectors of sizes  $9 \times 1$  and  $1 \times 9$ , this results in a total number of 9+9=18 trained parameters. As a consequence, kernel separability reduces the number of CNN model operations (such as the multiplication and the addition). A 2D kernel of  $k \times k$  applied for 2D signal with spatial dimensions of  $M \times N$  has a total number of  $(N-4)(M-4) \times k^2$  operations but in case of applying kernel separability yields 2(N-4)(M-4)k operations. The flow of separated convolution operations are summarized in Fig. 4.2. Fig. 4.3 represents the structure, denoted by Separated Convolutional Layer, used in the proposed method with kernel size of  $(M \times N)$  and satisfying the convolutional kernel separability. Separated Convolutional Layer is composed of three consecutive layers. The first convolutional layer has a kernel size of  $(M \times 1)$  and the number of convolutional neuron and filters are equal to the number of channels as the input feature map and the convolution operations are performed in a channel wise. The second layer operates in the same way as the first layer but it has a kernel of size  $(1 \times M)$ . The third layer is the convolutional layer with kernel of size  $(1 \times 1)$  and number of convolutional neuron is N. The collaboration of the three layers are connected to preform similarly to the convolutional layer with kernel size of  $(M \times M)$  and number of neuron and filter are the same as N but with large difference in the performance.

#### 2) Batch Normalization and Activation function

The proposed method follows the linear separable convolution kernels by a batch normalization and an activation function. Rectified Linear Unit (ReLU) is a nonlinear activation function that adds the nonlinearity to the model in order to allow it to be approximate to complex data. The proposed method employs the batch normalization which is described in [batchnorm]. Batch normalization algorithm is described as follows:

**Require:** : Minibatch activation values  $x : \mathcal{B} = \{x_{1,\dots,m}\}$ ; parameters to be learned  $\gamma$ ,  $\beta$ .

Ensure: 
$$\{y_i = BN_{\gamma,\beta}(x_i)\}$$

1: 
$$\mu_{\mathcal{B}} \leftarrow \frac{1}{m} \sum_{i=1}^{m} x_i$$

2: 
$$\sigma_{\mathcal{B}}^2 \leftarrow \frac{1}{m} \sum_{i=1}^m (x_i - \mu_{\mathcal{B}})^2$$

3: 
$$\hat{x}_i \leftarrow \frac{x_i - \mu_B}{\sqrt{\sigma_B^2 + \epsilon}}$$

4: 
$$y_i \leftarrow \gamma \hat{x}_i + \beta \equiv BN_{\gamma,\beta}(x_i)$$

where the batch normalization is performed for each layer independently such that  $\mu_B$  is the mean value for all ith channel of each sample and  $\sigma_B^2$  is the standard deviation value for all ith channel of each sample.  $\gamma$  and  $\beta$  are trainable parameters. In case of a single sample is processed by the model, which is not valid for calculating  $\mu_B$ ,  $\sigma_B^2$ , a moving average is calculated for  $\mu_B$ ,  $\sigma_B^2$  of each batch. So, the batch normalization algorithm for inference updated to:

**Require:** :activation values x; Calculated  $\mu_{\mathcal{B}}$  and  $\sigma_{\mathcal{B}}^2$  of all training minibatchs.

**Ensure:** : 
$$\{y_i = BN_{\gamma^{(k)},\beta^{(k)}}^{\inf}(x^{(k)})\}$$

1: 
$$E_x \leftarrow \frac{1}{m} \sum_{i=1}^m \mu_B$$

2: 
$$V_x \leftarrow \left(\frac{m}{m-1}\right) \frac{1}{m} \sum_{i=1}^m \sigma_B^2$$

3: 
$$y_i \leftarrow \frac{\gamma^{(k)}}{\sqrt{V_x + \epsilon}} x^{(k)} + \left(\beta^{(k)} - \frac{\gamma^{(k)} E_x}{\sqrt{V_x + \epsilon}}\right)$$

4: 
$$y_i \equiv BN_{\gamma^{(k)},\beta^{(k)}}^{\inf}(x^{(k)})$$

Batch Normalization [batchnorm] reduces the covariate shift produced as a result of moving between layers during the feedforward procedure [batchnorm]. Bach Normalization makes the landscape loss smoother and reduces the number of saddle points [bnopt] which allows to use higher learning rates. Using a higher learning rate makes the network training faster[batchnorm]. Batch normalization reduces the vanishing gradient problem and exploding gradient problem as it makes the resulted activation scale independent from the trainable parameter scale[batchnorm]. Batch normalization has the effect of regularization because of the inherited randomness when selecting the batch sample[batchnorm] which help the generalization to unseen chest X-Ray image.

As the proposed method uses the variants of ReLU [alexnet] extensively, where it is defined as f(x) = max(0, x). ReLU does not have saturation problem, like Sigmoid, which limits and prevents the trainable parameter updates.

#### 3) Deep and larger receptive field Network design

Deeper convolutional neural network design is a very important task for any image recognition task[resnet]. Training a deeper network is very expensive and has many challenges such as vanishing gradient problem, exploding gradient problem, and degradation problem [resnet]. Exploding gradient problem occurs when the gradient update becomes very large (approaching infinity) resulting in the network diversion. Vanishing gradient problem occurs when the gradient update becomes very small (approaching zero) resulting in preventing the parameter update for early layers[resnet] and preventing the network to learn new patterns. Batch normalization [batchnorm] and the use of ReLU activation function [alexnet] alleviate these two problems.

The deep layers of CNN networks sometimes need to approximate the identity function which is not a simple task especially with the existence of a nonlinear functions. Residual connection[resnet] overcomes this problem by using skip connection as shown in Fig. 4.4.

Fig. 4.4 represents the building block layer of the feature extraction phase, denoted by stack of Residual Separated Block (RSB). RSB consists of four layers of separated convolutional layers, each layer is followed by a batch normalization and an activation function. It has an output of depth N where each sublayer produces an output of depth N/4 which is concatenated at the end of the layer to produce a depth N. RSB produces a feature map that includes both low level features and high level features.

Unlike the traditional neural network, which is fully connected to the previous layer, convolutional neural network is connected locally to a local region of the previous feature map. This introduces the concept of the network receptive field [receptivefield]. Receptive field should be large enough to capture large patterns in the input chest X-Ray image. Therefore, any consecutive convolutional layers in the proposed method without a pooling layer in between a larger kernel size is used in one of them. Residual Separated block, RSB, in Fig. 4.4 may have kernel sizes of 3, 5, 7, and 9, respectively.

Fig. 4.5 Represent a complete CNN architecture.

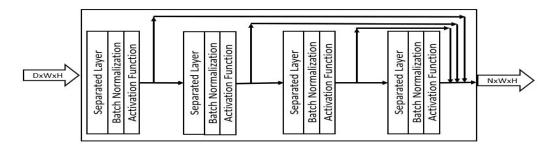


FIGURE 4.4: The stack of residual separated block (RSB) consists of four layer of separated convolutional layer each of which is followed by batch normalization and activation function.

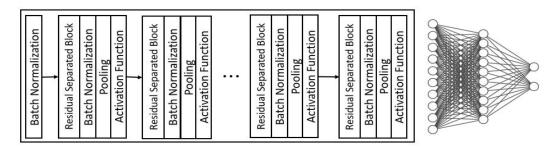


FIGURE 4.5: The complete proposed tailored CNN architecture.

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#### 5.1 Main Section 1

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## 6.2 Main Section 2

# Appendix A السيرة الذاتية لمقدم الرسالة

العنوان : سملا مركز

## Appendix B

## موجز الرسالة

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