A Simplified Convolutional Neural Network Design for COVID-19 Classification on Chest X-ray Images

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***Abstract*— COVID-19 is a respiratory virus that causes the spread of infection and has affected human around the world. The infection frequently results in pneumonia in human which can be detected using lung imaging, chest X-ray images. Deep learning models have been demonstrated to an effective COVID-19 interpretation on chest radiography. In this paper, we have proposed a simplified convolutional neural network model for COVID-19 screening that can classify the appearance of COVID-19 lesion into two classes. The proposed model; despite using fewer layers and the utilization of data augmentation approach in training process, can achieve the greater outcome. To evaluate the proposed model, we have used a partial of the public dataset, COVID-19 Radiography Database which is a collection of 13,808 chest X-ray images. At the final stage, the Grad-CAM visualization method has been used to enhance the important region of chest X-ray images in order to provide the explanations of COVID-19 predictions.**

Keywords—deep neural network, convolutional neural network, covid-19 classification, chest X-ray images

I. INTRODUCTION

COVID-19 is a transmissible disease, which is caused by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) [1]. Currently, the COVID-19 is an ongoing global pandemic, that has been spread around the world for over two years [2] especially the Omicron variant which is spreading more rapidly faster than the previous COVID-19 variant. Due to this, early detection and providing diagnosis is one of the most important steps to determining the severity, guiding the treatment, and allocating the limited resource for patients [3]. Currently, Reverse Transcription Polymerase Chain Reaction (RT-PCR), Computer Tomography Scan, and chest radiography are the standard procedures for COVID-19 screening. However, RT-PCR is the most time-consuming of all these three, whereas chest radiography, diagnostic imaging technology is the most common for COVID-19 detection due to its accessibility, portability, and affordable cost [4]. Therefore, in this study, we present a deep learning model for classifying COVID-19 on chest X-ray images.

The research and innovation of deep learning algorithms are becoming influential among medical image analysis tasks [5]. Several successful and practical deep learning models can assist clinicians in diagnosing the presence of disease and evaluating the severity of illness, such as skin lesion classification [6], brain tumor segmentation [7], diabetic retinopathy screening [8], and lung diseases detection [9]. To develop deep learning models for detecting and classifying COVID-19 lung infection on chest X-ray images, the help of a convolutional neural network-based algorithm can be used to implement a fast and accurate detection model [10].

Deep learning has previously been investigated for the detection and classification of COVID-19 on chest X-ray and CT-Scan images [11]. In 2020, the first deep learning open-source model for COVID-19 detection, called COVID-Net [12] was released to classify chest X-ray images into normal, pneumonia, and COVID-19. Then, there are numerous architectures of deep learning model have been presented for a specific task: ResNet [13], DenseNet [14], VGG [15], Inception [16], MobileNet [17], EfficientNet [18], and own modified or proposed model [19][20][21][22]. Moreover, developing new deep learning architecture can be supported by a variety of different objectives in order to make COVID-19 imaging analysis more understandable [23]. Hence, the novel custom architectures are often built with fewer parameters than the public model [24].

The aim of our work is to examine the capability of a simplified deep learning models for COVID-19 classification from chest X-Ray images, and data augmentation for improving the performance of our proposed model. We have developed our classification model from scratch by using a convolutional neural network and acquired data augmentation approach to avoid the overfitting and improve the model prediction accuracy [25] because data augmentation provides the various chest X-ray aspects which our proposed model can learn from the several image views.

The rest of this paper consists of five sections. Section II, we present the overview of our work, the detail of convolutional neural network, and the architecture of our proposed model. In section III, the detail of dataset, data pre-processing, data augmentation, and Grad-CAM method are described. Section IV presents the experimental setting, evaluation metrics, and experimental results. Finally, conclusions are pointed out in section V.

II. THE PROPOSED MODEL

A. Convolutional Neural Network

Convolutional neural network (CNN) is a powerful technique of deep neural network [26], most commonly applied to computer vision tasks. CNN architecture consists of three main types of layers, which are convolutional layer, pooling layer, and fully connected layer. The Convolutional

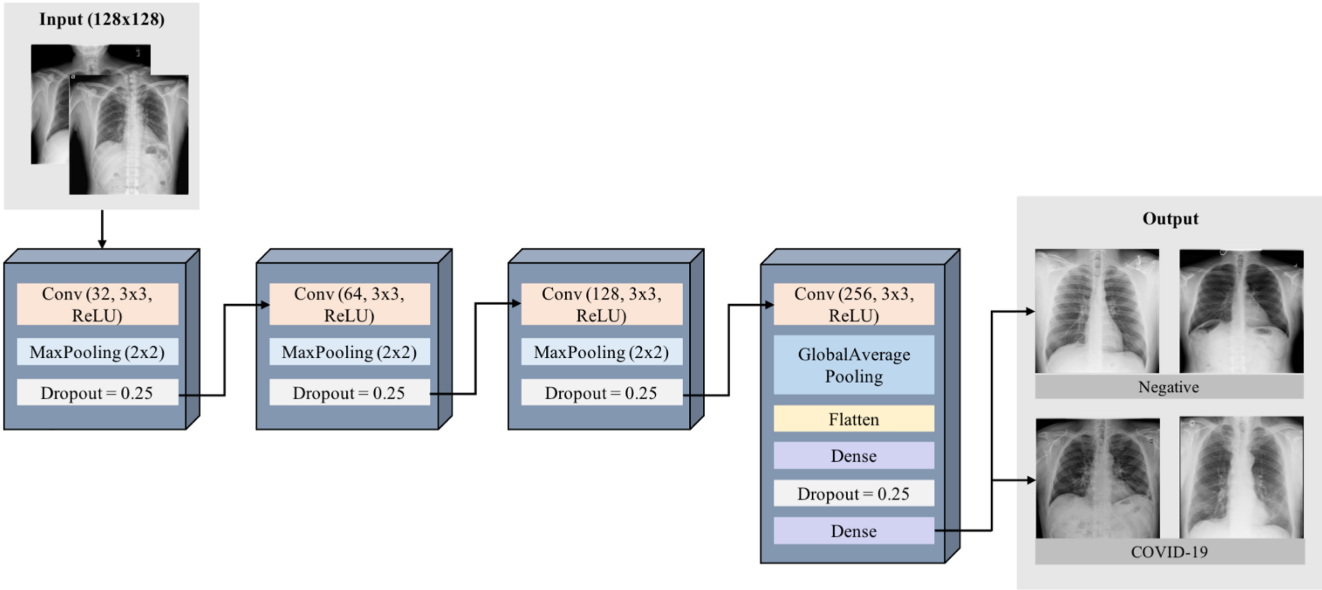

Fig. 1. The simplified convolutional neural network architecture of the proposed model

layer is the mandatory component of CNN, it is utilized to extract the features from images and provide the feature map for the subsequent layer. Along with the pooling layer, this layer could be used to reduce the dimension of the feature map, resulting in a decrease of network parameters. Finally, the last layer of CNN architecture is fully connected layer which receive the output features from the final convolutional or pooling layer and train non-linear combinations of these feature maps in order to categorize them into various classes [27].

B. *The architecture of the proposed model*

In this work, we proposed a fast and efficient convolutional neural network model for binary classification on chest X-ray images. The output of the proposed model provides the class of COVID-19 appearance as negative class for no finding of COVID-19 pneumonia and positive class for COVID-19 pneumonia appearance. Our proposed model has been constructed from four convolution layers, three max pooling layers, four dropout layers, five activation function layers, one global average pooling layer, one flatten layer, and two fully connected layers. The Rectified Linear Unit (ReLU), the activation function was defined for all convolutional layers except the last fully connected layer, the sigmoid activation function was applied for binary classification. These layers were reduced substantially from the regular public models. The total parameter of the proposed model is 393,522 and the number of layers is 23. The architecture of the proposed model is shown in Fig. 1. The detail of hyperparameter for training our model is presented in Table I. While, the initial parameters were generated randomly.

III. METHODOLOGY

This section presents the methodology of COVID-19 classification. The detail of the dataset, data pre-processing, data augmentation, and the visualization output using Grad-CAM method which we used in this study was described.

A. *Dataset*

The COVID-19 Radiography Database is the collection of chest X-ray images which belong to the COVID-19 positive patients, normal, lung opacity, and viral pneumonia cases, available on Kaggle [28][29]. In this work, we used a partial of this dataset for binary classification task between the chest X-ray of COVID-19 cases and negative cases. This collection of the dataset contains a total of 13,808 chest X-ray images, of which 3,616 are COVID-19 positive images and the remaining 10,192 are COVID-19 negative images. Fig. 2 shows a sample of chest X-ray image of negative class and COVID-19 class from the dataset.

TABLE I. THE LIST OF HYPERPARAMETER

Hyperparameter	Detail
Number of epoch	200
Number of layer	23
Conv filter size	3x3
MaxPool filter size	2x2
Batch size	256
Optimizer	Adam
Learning rate	0.0001
Loss function	Binary cross-entropy
Activation function	ReLU for Conv Layer Sigmoid for Fully Connected

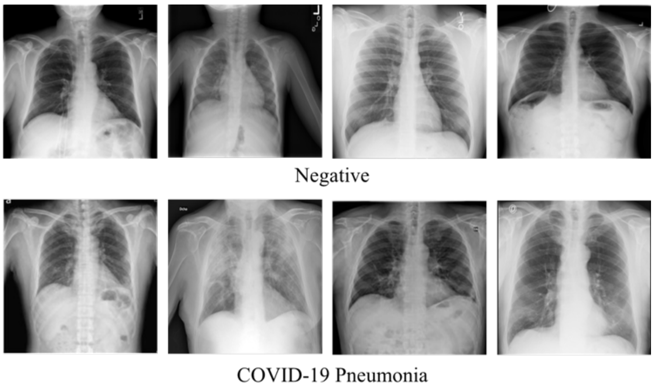

Fig. 2. Example of chest X-ray images of negative cases (top) and positive cases (bottom)

B. Data pre-processing

Before training the model, we resized all images based on the input layer from 299x299 to 128x128 and normalized each image with 255 to transform the image to the range of [0, 1].

C. Data Augmentation

Data augmentation is a frequently used method for the images in training set which can transform the images into several perspectives by using a variety of pre-processing approaches [30]. The number of samples can also be increased by a synthetic image when the dataset contains the imbalance number of images among the classes [31]. One additional reason to apply data augmentation method is that it prevents the model to avoid the overfitting problem by acquiring semantic information and another view of images during training the model [32]. In this work, we apply nine techniques to the images, vertical flip, cropping, rotation, random brightness, random contrast, random fog, transpose, random sun flare and RGB shift. Fig. 3 presents the example of chest X-ray images when the data augmentation was applied. These augmented images will be generated randomly in each epoch during training process.

D. Visualization of Convolutional Neural Network using Grad-CAM

Numerous researchers attempt to make deep learning more understandable and describable. It is essential in improving the interpretability of the deep learning model in several applications that are related to medical imaging. Gradient Weighted Class Activation Mapping (Grad-CAM) was introduced to facilitate the explanation of deep learning models [33]. When performing a prediction, the Grad-CAM generates a visual explanation for fully connected layer and provides map enchantment for interpreting the information from the model.

In this work, we applied the Grad-CAM to the last convolutional layers and chose the colormap from Matplotlib library. The gist_rainbow colormap was chosen for explaining our model. Fig. 4 shows the shading of gist_rainbow colormap in which the red and the magenta tone will be used to identify the important regions such as the lung opacity of COVID-19.

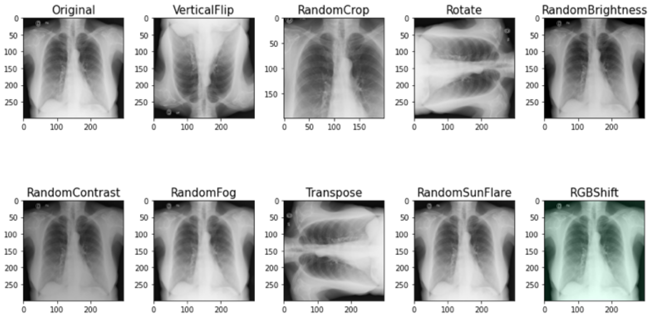

Fig. 3. Example of augmented chest X-ray images

Fig. 4. gist_rainbow colormap

TABLE II. THE NUMBER OF IMAGES IN EACH DATASET

Dataset	COVID-19 Classes		Total
	Negative	*Positive*	
Training	7,287	2,654	9,941
Validation	844	261	1,105
Test	2,061	701	2,762
Total	**10,192**	**3,616**	**13,808**

IV. EXPERIMENTS

This section presents our experimental setting, evaluation metrics that were used to evaluate the classification performance, and the results of this study. The proposed COVID-19 classification model has been implemented in Python with TensorFlow and Keras API backend. Tesla P100 and 13.6 gigabytes of RAM on Colab Pro were used to run the model during training time.

A. Experimental setting

The dataset was separated 20% of the total images into the test set, with the remaining 80% which was divided into the training set (70%), and the validation set (10%). Table II shows the distribution of the images in each partition set.

In practice, the interpretation of COVID-19 pneumonia finding on chest radiography, especially for serious complication cases, the false negative should be minimized to avoid the misidentification as COVID-19 pneumonia appearance to no finding appearance. There are several ways to improve the classification performance and reduce the false negative and false positive values, one potential approach which was applied in this study, is data augmentation. The outcome of data augmentation approach provides the various aspect of chest X-ray images to our model during training process. However, the horizontal flip was not applied to our training set, because we concern about the dextrocardia with situs inversus conditions [34], the abnormal positioning of the heart.

B. Evaluation metrics

To evaluate our proposed model, we adopted the accuracy, precision, recall and F–measure that were used to compute the classification performance of the model and the equation as shown in (1) – (4).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F - measure = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{4}$$

Where TP, TN, FP, and FN refer to True Positive, True Negative, False Positive, and False Negative, respectively.

In this study, accuracy indicates how many the proposed model can correctly classify the chest X-ray images into negative and positive classes. Precision is the proportion of patients that we correctly detect as COVID-19 positive out of all the patients who were predicted to positive. Recall refers to how many the model correctly identifies chest X-ray images of positive cases. Furthermore, F–measure was used to balance the precision and recall value.

C. Results

We compare the performance of the proposed model with confusion matrix of the test set when we trained the model without applying the data augmentation approach (Fig. 5) and when the data augmentation was employed in training process (Fig. 6). Fig. 6 shows that the number of false negative cases were decreased from 67 to 27 and the number of false positive cases were also reduced from 39 to 24. It can be seen that using data augmentation can improve the classification performance for our proposed model by minimizing the false negative and false positive due to the providing of several views of chest X-ray images in training set.

Table III presents the comparison of classification performance between training the model with the original dataset and training the model along with augmented images. The precision, recall, F–measure, and accuracy of training, validation, and test set were all improved when the data augmentation method was used throughout the training process. Therefore, we achieve the training accuracy from 98.96% to 99.98% whereas validation accuracy is increased from 96.02% to 98.19%. Also, the inference model on the test set can classify the negative appearance and pneumonia appearance of COVID-19 correctly from chest X-ray images. The accuracy of the test set in final stage is 98.15%.

Fig. 7 and Fig. 8 show the trend of training and validation accuracy and loss values of the proposed model, respectively which was trained with the augmented images. In addition, to visualize the prediction of the proposed model, we applied Grad-CAM to provide the localization map by highlighting the area of interest with high-intensity visuals in red and magenta color as shown in Fig. 9.

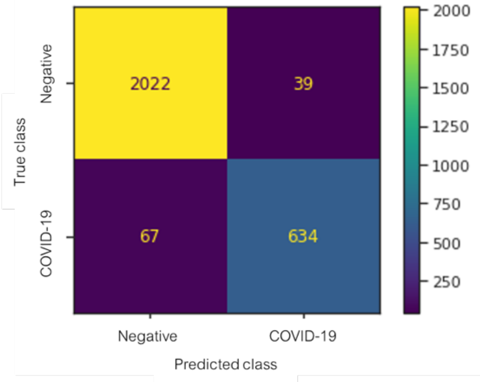

Fig. 5. Confusion matrix of the proposed model on the test set without data augmentation approach.

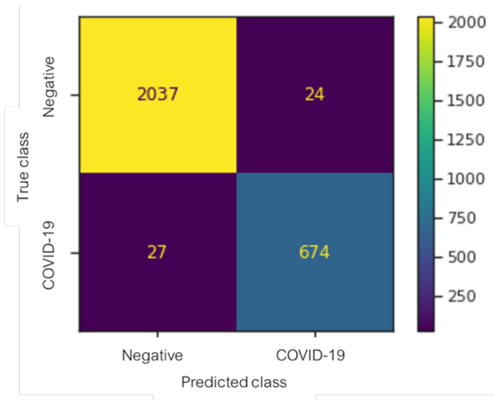

Fig. 6. Confusion matrix of the proposed model on the test set with data augmentation approach.

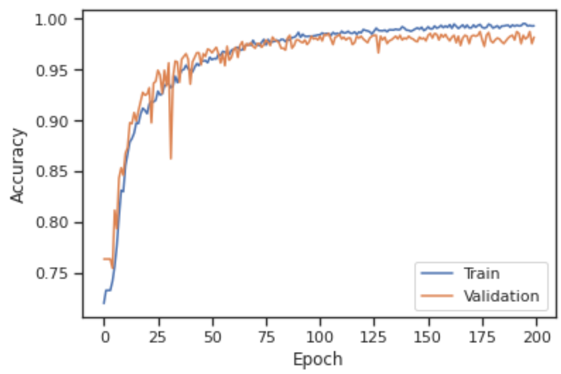

Fig. 7. Training and validation accuracy of the proposed model.

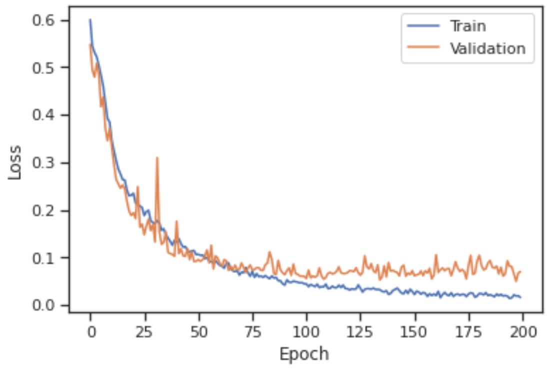

Fig. 8. Training and validation loss of the proposed model.

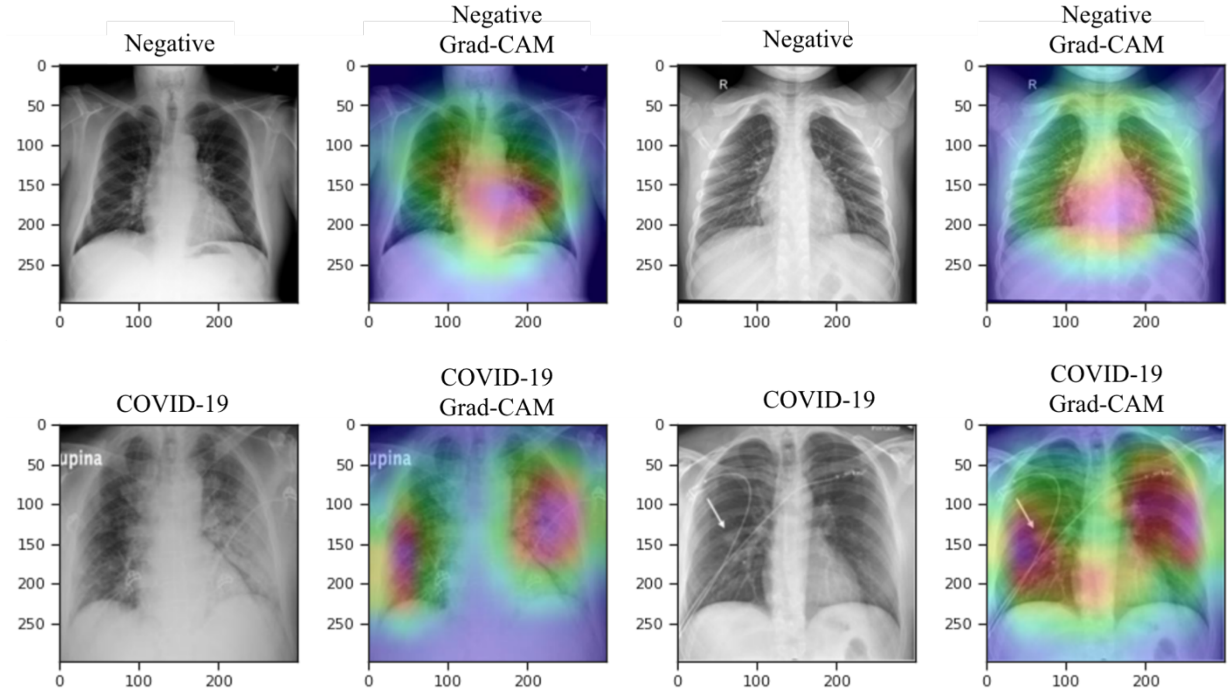

Fig. 9. Visualization of chest X-ray images using Grad-CAM on the trained model. The sample of original images and the corresponding activation map of negative appearance (top) and COVID-19 appearance (bottom).

TABLE III. THE EVALUATION OF COVID-19 CLASSIFICATION

Model	*Precision*	*Recall*	*F-measure*	*Accuracy*
Training set				
Proposed model	0.9837	0.9774	0.9805	0.9896
Proposed model with Data Augmentation	1.000	0.9992	0.9996	0.9998
Validation set				
Proposed model	0.9255	0.9042	0.9147	0.9602
Proposed model with Data Augmentation	0.9617	0.9617	0.9617	0.9819
Test set				
Proposed model	0.9421	0.9044	0.9229	0.9616
Proposed model with Data Augmentation	0.9656	0.9615	0.9635	0.9815

In case of model predicted to negative patients, the high-intensity visual will be located at the heart between left and right lung. While, positive patients, the class activation map will establish the high-intensity area where some opacity or white spots were found on the chest X-ray images.

Based on our results, we have compared the performance with the lightweight CNN models such as MobileNet [35] and EfficientNet [36]. Our proposed model has 393,522 parameters while MobileNetv1 has approximately 4.2 million parameters and EfficientNet-B0 has 5.4 million parameters. The accuracy on the test set with data augmentation of MobileNetv1 is 98.95%, whereas EfficientNet-B0 is 99.38%. Although the accuracy of our model is slightly lower than these two models, it has the advantages of having a smaller architecture, using fewer parameters, and providing faster calculations.

V. CONCLUSIONS

In this work, we have demonstrated how a simplified deep convolutional neural network can be employed to classify the chest radiography between COVID-19 appearance and negative for COVID-19 appearance. Although the deeper CNN models provide higher accuracy, our proposed model, which employs a lightweight architecture, can deal with the COVID-19 classification task in a timely and accurate manner. To generate the explainable localization map of our proposed model, we applied the gradient-weighted class activation mapping into the final convolutional layer for emphasizing the relevant regions and displaying the feature map of each class in heatmap scale. The overfitting of the model was prevented by data augmentation method which can provide the diversity of chest X-ray images for training the model. We expect that the integration of our model with appropriate image pre-processing and data augmentation methods could be adapted to the classification task on the other type of medical images.

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