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A Basic Concept of Image Classification for Covid-19 Patients Using Chest CT Scan and Convolutional Neural Network

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Abstract— On March 12, 2020 WHO announced the status of a global pandemic related to the increasing Covid-19 cases. The outbreak has hit around 188 Countries. Healthcare professionals have repeatedly performed laboratory tests to get the right results to patients, such as, check the chest CT images of the patient's lungs. This is an essential role in clinical treatment and teaching task. In this paper, we tried to classify chest CT image of Covid-19 patient. CNN produce spatial characteristic from images so it very expeditious way for image classification problem. Three techniques are evaluated through experiments. The results of the experiments show the test set has 1119 Covid-19 chest CT images and 446 normal chest CT images. The experiment results represent that our offer model delivered the highest accuracy score of 97.57% among the other models, Inception ResNet-V2 and Inception-V3.

Keywords— image classification, convolutional neural network, image processing, machine learning, covid-19

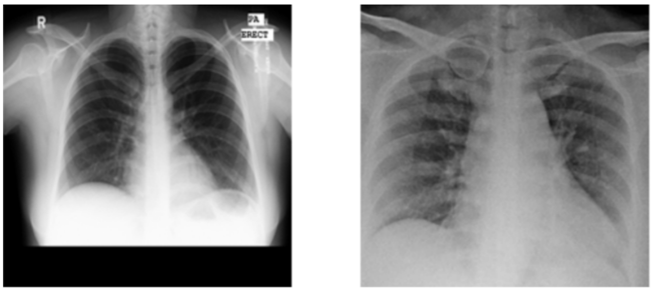
I. INTRODUCTION

Unfamiliar pneumonia has been reported at Wuhan, China on December 2019 [1]. This virus was found, then it was contaminated human, on 6 January 2020, and then well-known with named Covid-19 or Coronavirus [2]. 21,549,706 cases was recorded as Covid-19 pneumonia in 188 countries at 17 August 2020 [3]. Figure 1 is a map of Covid-19 covered area.

Covid-19 is expected to produce acute respiratory distress syndrome (ARDS) [1]. After 10 days onset of symptoms, chest CT reveals greatest severity and lung abnormalities on [4]. Real-time turn over transcription-polymerase chain reaction (RT-PCR) such swabs, phlegm, tracheal aspirates is a general test to recognize Covid-19 virus in the human body [6]. Ai T et. al [7] discover a fact that 42% patient's chest CT scan can help to detect condition improvement of patients before they took a RT-PCR.

Fig. 1. The Map of Covid-19 [5]

Chest CT scan can be illustrated wrecking of lungs before reported coronavirus infection. We can see in Figure 2, the normal chest CT scan and covid-19. But not all of patients with Covid-19 pneumonia steadfastly denoted no hypoxemia or respiratory impediment during hospitalization. The first diagnosis until patient recovery must been analyzed to determination of alteration in chest CT detections linked with Covid-19. This is an essential role in clinical treatment and teaching task.



(a) (b)

Fig. 2. a) Normal b) Covid-19 [8]

In this paper, we tried to classify Covid-19 patient establish from chest CT scan image with deep learning techniques: Convolutional Neural Network (CNN). CNN can

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solve image classification problems efficiently by generating spatial features from images.

II. Literatur Review

Recently, researchers have been widely used a machine learning model to invent vision characteristic from chest-CT scan for Covid-19 identification named as COVNet [9]. Visual features of pneumonia and normal (non-pneumonia) lung diseases have been developed. The severity level of this Covid-19 can be categorized by COVNET.

The image pattern chest CT scan for identifying Covid-19 is developed by Xie et al. [10]. The data shows that 5 from 167 patients are tested negative RT PCR for covid-19 detection. Fang et al. [11] does some researches on the sensitivity of RT PCR and chest CT during covid-19 detection by tracing and analyzing the two patients' travel history and symptoms. The results are chest CT scan is higher than RT PCR for covid-19 diagnosis. Chest CT scan is better than RT PCR.

The 121 contaminated patients' chest CT scan from different centers in Tiongkok has been analyzed by Berheim et al. [12]. They used deep learning techniques on it. The severity level of disease increases with time from onset of symptoms and designated the signs of disease.

Gozes et al. [13] has studied an artificial intelligence derived from CT examination tool on covid 19 detection and qualification. Slice of opacities in the lungs automatically has been extracted by them. The evolved system obtained 98.2% sensitivity and 92.2% specificity. Result of the system gives quantitative opacity measure and 3D volume present for bluredness.

In our research, we tried to classify chest CT of Covid-19 patient based on convolutional neural network with a large number of chest CT scan, amount 5216 dataset image. While in the earlier research, it only used hundreds of datasets. Convolutional neural network can extracts spatial features image. We compared our proposed model with the other methods, for example, start with resnet-V2 and inception-V3.

III. Materials and Methods

A. Development Environment

In this paper, we propose to classify chest CT of Covid-19 patient using Google Collaboratory included Keras API with Tensor Flow. Convolutional Neural Network (CNN) architecture using Python has been implemented in our model.

B. Image Processing

We are amended all our training, validation and evaluation set to 32*32*3 to adapt in our model. We are operated some pre-processing before training the images in convolutional neural network to decrease the complexity and increase accuracy.

C. Dataset

The chest CT dataset was used in our research. We obtain a 5216-image dataset. These images are labelled as two categories, one types is covid-19, and the other one is a normal image. All the image was then divided into a training set (3651), a validation set (1565). The training set is used to train the weights of the built deep convolutional neural network. The validation set is used to verify the generalization capability of the model, and the model weights are chosen to put away according to the loss function value on the validation set. Saved model weights are tested by the test set to acquire the test results of the model. Table I shows the sample images of each class.

TABLE I. Dataset

Category	Sample of size
Training Set	3651
Validation set	1565
Total dataset	5216

D. Convolutional neural networks (CNN)

Image classification may use CNN [14] as a powerful method. Dilbag Sing et. al [15] has been elaborated the structure and usefull feature extraction characteristics which is making an image transforms into CNN as a dynamic model for image classification. They reported that CNN layers are arranged three dimensions: width, height, and depth. Limited neuron is being attached only by the neurons in the given layer. Reducing probability score vector and depth dimension coordinating are the output in CNN. Fig. 2 shows the training and testing frameworks of the deep convolutional models for COVID-19 classification. The CNN classifier which is utilized kind of layers for model building and testing goal are being demonstrated in fig. 2.

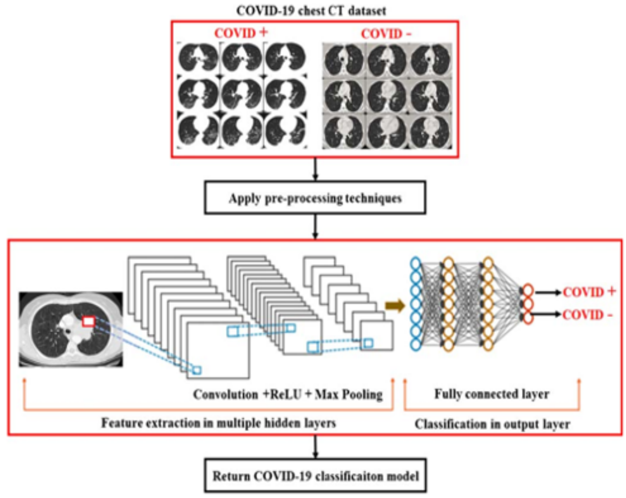

Fig. 3. Diagram of the training process of the CNN-based COVID-19 classification model [15]

Classification of Covid-19 infected patients and features of chest CT images are used to accurately classifying the patients whether they belong to infected Covid-19 class or not. Repeated classification calculations and computations are involved in the process of chest CT image-based COVID-19 from disease classification using CNN model [15]. In another experiment, [16] specifics of layers in CNN has been described as follows:.

- Convolutional Layer
  Computational work basic building of block Convolutional Neural Network is done by convolution layer. the depth, stride and padding are determined by three parameters. The Output size of a convolutional layer is:

$$o = \left(\frac{n + 2p - f}{s} + 1 \right) x \left(\frac{n + 2p - f}{s} \right) \quad (1)$$

where p = padding, s = stride, f = number of filters, n = image width = image height, o=output size (w*h).

- Max Pooling Layer
  Non-overlapping sub-regions of the input features applies a max filter to develop the Max-pooling technique. Max-pooling may decrease the dimensionality of the features. The Output Size of a Max-Pooling layer is:

$$o = \left(\frac{nw - f}{s} + 1 \right) x \left(\frac{nh - f}{s} \right) \quad (2)$$

where, s = stride, f = number of filters, nh = input height, nw = image width, o = output size (w*h).

- Dropout Layer
  A dropout layer randomly that gave probability with zero input elements. Over-fit on neural networks algorithm may increase by using dropout as a method [16].
- Fully Connected Layer
  A layer that can represent a feature vector for the input named by fully connected (FC) layer. The significance of information for input can be saved by the feature vector [17].
- Softmax Layer
  Softmax layer is a layer that show the decimal probabilities in multi-class classifications. This probability must add up to 1.0 [18].

IV. Result and Discussion

A. Test Result

The test set is used to evaluate the generalization ability of the trained model use the test set. The test set contains 1119 Covid-19 chest CT images and 446 normal chest CT images. Table II. show the results of the test.

TABLE II. TEST RESULT

Classification	Covid-19	Normal
Total result	1119	446

Training, validation and evaluation are parts of our dataset. The dataset in the convolutional neural network model is trained by using the training and the validation sets. the performance of the trained model is being evaluated by using the evaluation set. The following formula is used to measure The accuracy [19].

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+FN+FP+TN}} \quad (3)$$

where TP = True Positive, TN = True Negative, FP = False Positive, FN = False Negative.

Two indicators have been taken to evaluate the classifying performance are recalled rate and precision. Precision is assigned as P = TP / (TP + FP). Recall is assigned as R = TP / (TP + FN). F1 score is assigned as F1= 2PR / (P + R). Thus, the precision rate is 98%. The recall rate is 98%. F1 value is 98%.

We can see accuracy, loss, and mean absolute error (MAE) the curve of our proposed model in figure 4, 5 and 6.

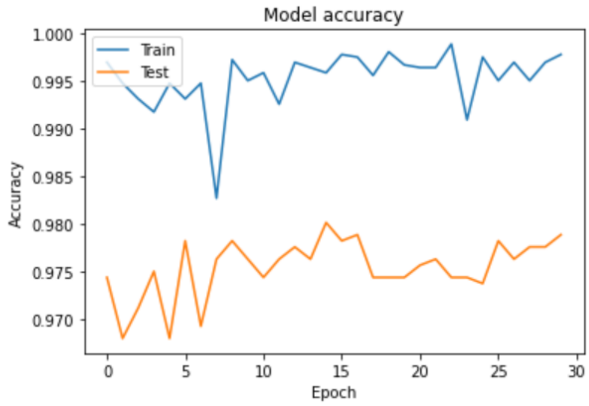

Fig. 4. Model Accuracy

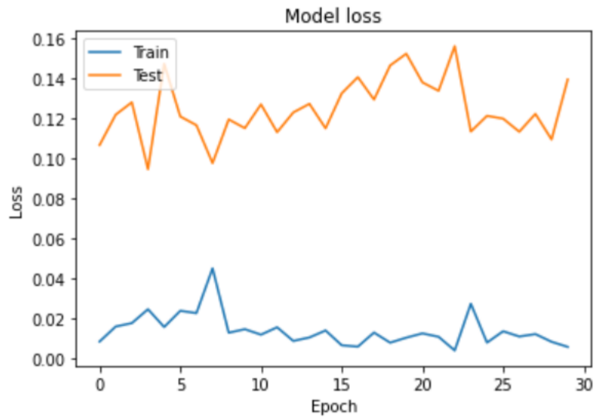

Fig. 5. Model Loss

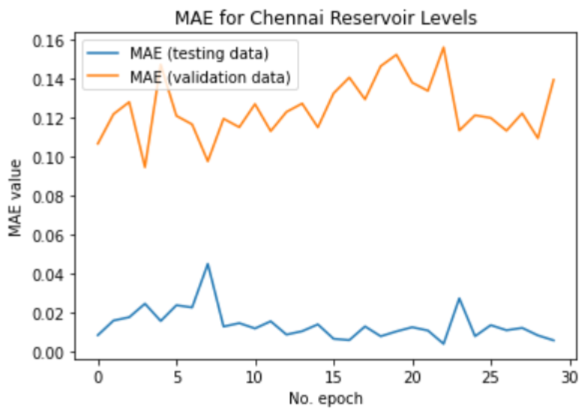

Fig. 6. Model Accuracy

As shown in Fig. 4, 5 and 6, there is a space in the middle of validation and train accuracy which reduced after several epochs so there is low overfitting. We also see that the loss curve is decreased, after several epochs. MAE to be the official loss value. Loss and Val loss can be implemented in the history object.

B. *Comparison results classification methods*

We compared our result with two other methods, Inception Resnet-V2 and Inception-V3. The results are displayed in Table III.

TABLE III. COMPARISON OF ACCURACY CLASSIFICATION METHOD

Model	Acc	Rec	Pre	F1
Inception ResNet-V2 [20]	87	84	91	86
Inception-V3 [20]	97	94	100	96
Propose Approach	97.57	98	98	98

As shown in Table III, we released the results and other methods in reference [20]. Our proposed model has better accuracy, recall, precision and F1 than the others. We get the accuracy of about 97.53%. The lowest accuracy is Inception-ResNetV2 about 87% values.

V. CONCLUSION

We concluded that CNN-based approach and using chest CT scan images: Covid-19 and normal can forecast Covid-19 patients automatically. The test set contains 1119 Covid-19 chest CT images and 446 normal chest CT images. In the performance results issue that our model, be the highest accuracy of 97.57% among the other methods. In future research, image classification with CNN method for Covid-19 can be tested with a very large dataset and complete with symptoms.

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