Cona Detect - Analyzing COVID-19 Patients Automatically Based on Chest X-ray Images Using a Deep Neural Network Model

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Abstract— **The COVID-19 pandemic is considerably more than a health disaster, it makes a big impact on all of the fields such as economy, education, and health care all over the world. Until now, no vaccine can cure COVID-19 patients effectively and successfully. Each nation designs its treatment regimen to help patients get over the disease. This pandemic spreads out unexpectedly, with a quick infection. To reduce the number of cases, detecting the positive cases and quarantining them needs to be done as early as possible to prevent further spread. Most of the nations are running out of test kits and materials for detecting. The lack of resources and the rise of daily cases all around the world encourages us to come up with a Deep Learning model that can be used to recognize COVID-19 positive cases using chest X-rays images of patients, as well as other pneumonia infections. In this research, we propose Cona Detect, which is a CNN model, to diagnose and identify COVID-19 positive cases based on patients' chest X-ray images. ResNet101 is the architecture that has been used for the proposed model. By using a dataset prepared by collecting the chest images of COVID-19 patients and others chest pneumonia X-ray images, such as bacterial and viral problems, the proposed model will use those to train and give out the prediction of the images based on the test images, finally calculating the accuracy of the model. Cona Detect has been trained and tested on the prepared dataset and the preliminary results prove that our proposed model obtained an overall accuracy of 91.43% (using ResNet101), and more importantly, the precision and f1-score rate for COVID-19 cases are 95% and 97% respectively for 4-class cases (COVID-19 versus Normal versus Pneumonia-bacterial versus Pneumonia-viral). Overall, the proposed model essentially offers the current radiology based methodology, and during the COVID-19 pandemic, it can be a truly effective tool for diagnosis, and follow-up of COVID-19 cases, as well as identifying other pneumonia symptoms.**

Keywords—COVID-19; Automated; Deep Neural Network; chest X-ray images

I. Introduction

At the end of December 2019, the Coronavirus or COVID-19 was first reported in Wuhan, China. It belongs to the family of viruses "Coronavirus" (CoV), then was called "Severe Acute Respiratory Syndrome Coronavirus 2" (SARS-CoV-2). Until February 2020, the World Health Organization (WHO) has named it COVID-19 [1], [2]. On 30 January 2020, it was declared as a Public Health Emergency of International Concern. Finally, WHO declared the COVID-19 outbreak as a pandemic [3]. After the outbreak, the number of daily cases began to rise exponentially and reached 24 million cases, and around more than 800 thousand deaths globally by 27 August 2020 [4].

When has been infected, a COVID-19 victim may develop numerous signs of infection including fever, cough, and respiratory illness. In severe cases, the infection may cause pneumonia, trouble breathing, multi-organ failure, and even death...[5]. Due to the speedy growth rate of the COVID-19 cases, the health system of many countries has been on the verge of collapse. They are now suffering from a lack of testing kits. Many countries have declared total lockdown and asked its residents to stay inside and strictly avoid gatherings.

To fight COVID-19, a crucial step has been made, which will be the effective screening of infected patients, to isolate and treat positive cases. Recently, the real-time reverse transcription-polymerase chain reaction (rRT-PCR) is the main screening technique to find out COVID-19 [6]. The analysis is diagnosed with respiratory samples of the patient and within a few hours to 2 days, the results can be ready. Researchers noticed that COVID-19 patients' lungs have some visual marks like ground-glass opacities — darkened spots which can help to distinguish between COVID-19 patients and none infected ones [7]. The researchers acknowledge that chest radiology based systems would be an efficient tool in the detection and follow-up of many COVID-19 cases.

Recently, researchers from all of the nations, from various subjects are struggling the entire day to deal with this pandemic [8]. Many of them have written preprint articles illustrating strategies for COVID-19 detection from X-ray images. These plans have achieved encouraging outcomes on a small number of images but it does not mean that they are ready to become a production of solutions. That is the reason why those still require careful analysis and development before putting them into real life. A great number of researchers and data scientists are working concurrently to build highly precise and stable deep learning-based approaches for the analysis of COVID-19 positive cases [9]. Deep learning techniques is one of the essential ways that researchers are concentrating on identifying any special features from chest radiography images of COVID-19 patients. Deep learning has been very successful in numerous tasks involving medicinal model study as well in the past [10].

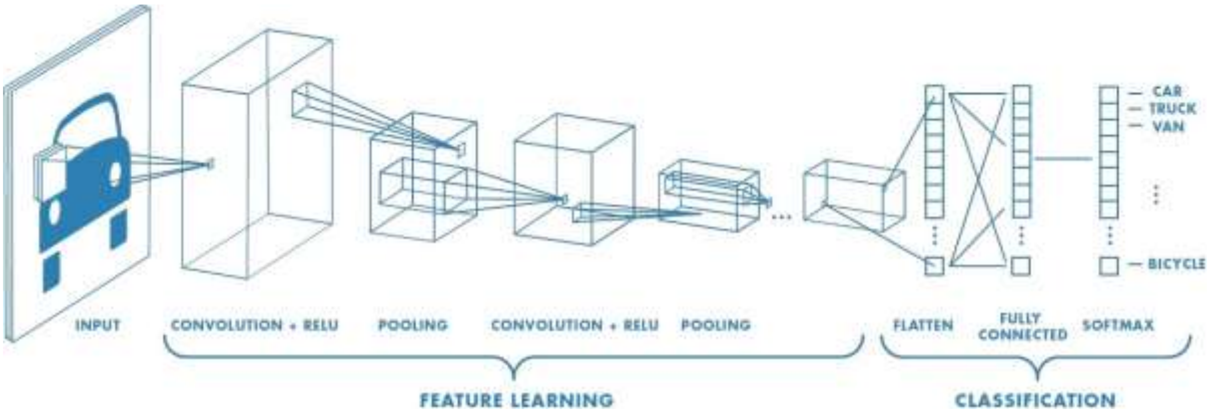


Fig. 1. Visualization of Convolutional Neural Network (CNN) architecture.

AI techniques in analysis patients in the medical field automatically are getting popular and successful lately. With the speedy increase in the total number of COVID-19 positive cases, the requirement of AI-based automated discovery and examination systems is becoming more and more hurry due to the demand for doctors and researchers.

In this study, we present a deep learning-based method to recognize COVID-19 infection from chest X-ray images. This model suggests a deep Convolutional Neural Network (CNN) model classifying three different kinds of Pneumonia; specifically COVID-19, bacterial pneumonia, viral pneumonia respectively. Cona Detect is our proposed model name and it will help everyone distinguish the difference between three types of pneumonia infections and how COVID-19 is different from the others. Until now, this model does not fully replace the existing testing method, it can still be used to decrease COVID-19 cases that need quick testing or additional review from experts. Moreover, it would be a great combination to deal with the limit of testing kits, thanks to the diagnose of Cona Detect.

II. Model

A. *Deep neural networks*

The Deep Neural Network is a kind of machine learning (ML) and artificial intelligence (AI) that reflects the process people get information [11]. It is also a technology developed to reproduce the movement of the human mind, namely classifying patterns and transferring input information across different layers of simulated neural connections. It is a network with an input, output layer, and at least one hidden layer in between, use to process unlabeled or unorganized data. The phrase "deep learning" is also used to represent these deep neural networks, because deep learning describes a kind of machine learning which is technologies that use perspectives of artificial intelligence to inquire to analyze and coordinate information.

B. *Convolutional Neural Network*

Convolutional Neural Network (CNN) is a deep learning technique consisting of complicated layers of overlap, using local connections known as local receiving fields, and sharing weights for performance and efficiency. Deep architecture helps these networks learn many complicated features that a simple neural network cannot study [12]. A reliable neural network is a core powering computer vision with a diversity of forms. The principal theory of CNN is to get local characteristics from an input (usually pictures) in higher layers and lower layers, it merges them into more complex features. A CNN architecture consists of three layers: Convolutional Layer, Subsampling (Pooling) Layer, and Fully connected layer which can be shown in Fig. 1..

C. *Residual neural network*

The residual neural network (ResNet) is a complicated neural network, using a consistent connection to cross one or more layers [13].

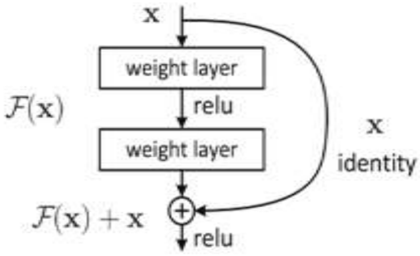


Fig. 2. Residual Block of ResNet network.

ResNet-101 has a depth of 101 layers. It can sort models into 1000 types of things, such as keyboards, rats, pencils, and several creatures. Therefore, the network detected the feature-rich illustrations for multiple kinds of images.

ResNet is very alike to networks including convolution, pooling, activation, and fully-connected layer. Fig 2. shows the residual volume used in the network. A curved arrow arrives from the start and finishes at the end of the residual mass. Where $H(x)$ is the predicted value, $F(x)$ is the actual value (label), we need $H(x)$ to be equivalent to or around $F(x)$. $F(x)$ can be obtained from x as follows:

$$x \rightarrow weight\ 1 \rightarrow relu \rightarrow weight\ 2$$

Get $H(x)$ by:

$$F(x) + x \rightarrow relu$$

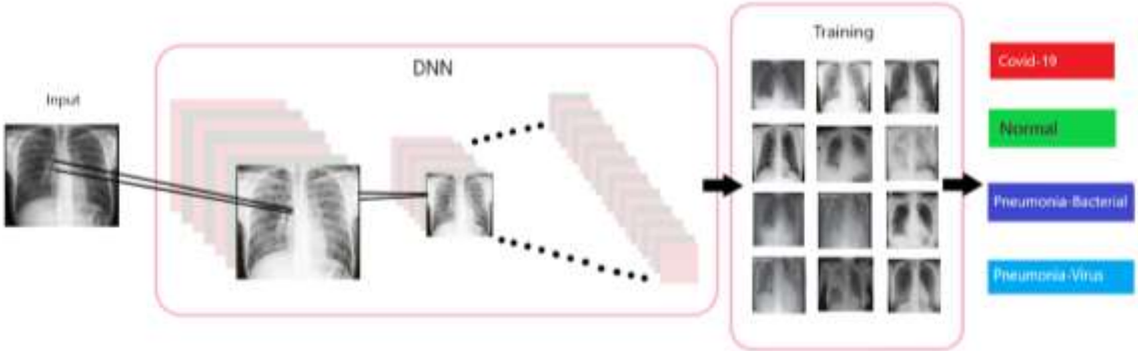


Fig. 3. Overview of the proposed model and methodology.

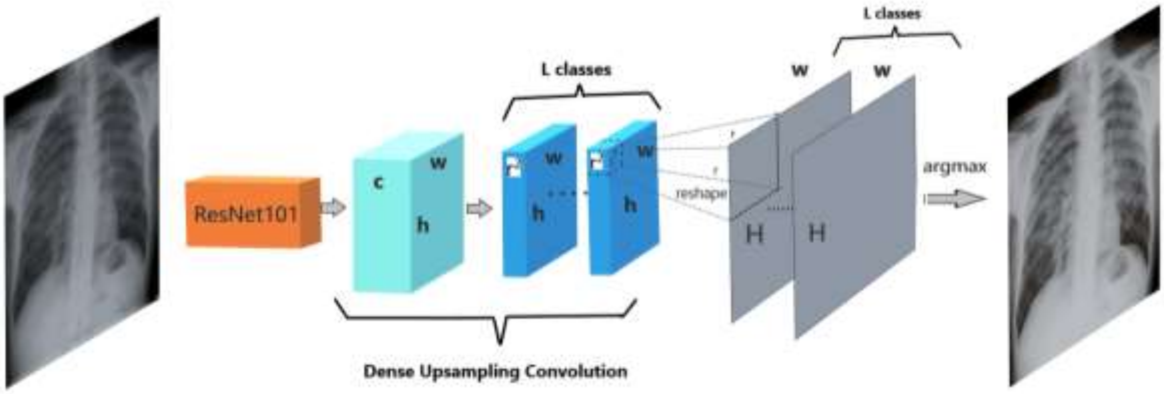


Fig. 4. Visualization of the ResNet101 architecture in Cona Detect proposed model.

D. *Proposed model*

Cona Detect is a CNN architecture model for identifying COVID-19 patients based on their chest X-ray images, as well as other pneumonia diseases such as by virus or by bacterial. The proposed model is illustrated in Fig. 3. and Fig. 4.

As can be seen in Fig. 3 and Fig. 4, the model will initial scan through each element of input, which is the patient's chest X-ray images dataset provided (COVID-19, normal, pneumonia-bacterial, and pneumonia-viral respectively), by DNN method. It is a combination of various units and the signal will be processed in layers (the next layer will get the output of the past layer for processing). The process will perform one at a time until the end. Next, training with a separate dataset with X-ray images of the affected lung or normal lung to check the correctness. Finally, the model will give out the result based on the accuracy and the loss when training and when validating the test images.

III. EXPERIMENTAL EVALUATION

A. *Dataset description*

Since COVID-19 is the latest virus, there is no proper dataset available which can be applied for this research. Consequently, we had to build a dataset by getting chest X-ray images from two different publicly accessible image databases, which are available at an open-source GitHub repository.

There will be 2139 chest X-ray images in total, including 4 types: X-ray images of COVID-19 patients, X-ray images of normal person, X-ray images of patients having pneumonia-bacterial disease and X-ray images of patients having pneumonia-viral disease. The dataset summary is displayed in Table I.

TABLE I. DATASET SUMMARY

Disease	Number of chest X-ray images
COVID-19	321
Normal	945
Pneumonia-bacterial	449
Pneumonia-viral	424

After collecting the dataset, the images will be separated into two parts: One for training and the other for validating. So there will be:

286 COVID-19 images for training, and the others for testing.

845 normal images for training, and the others for testing.

374 pneumonia-bacterial images for training, and the others for testing.

354 pneumonia-viral images for training, and the others for testing

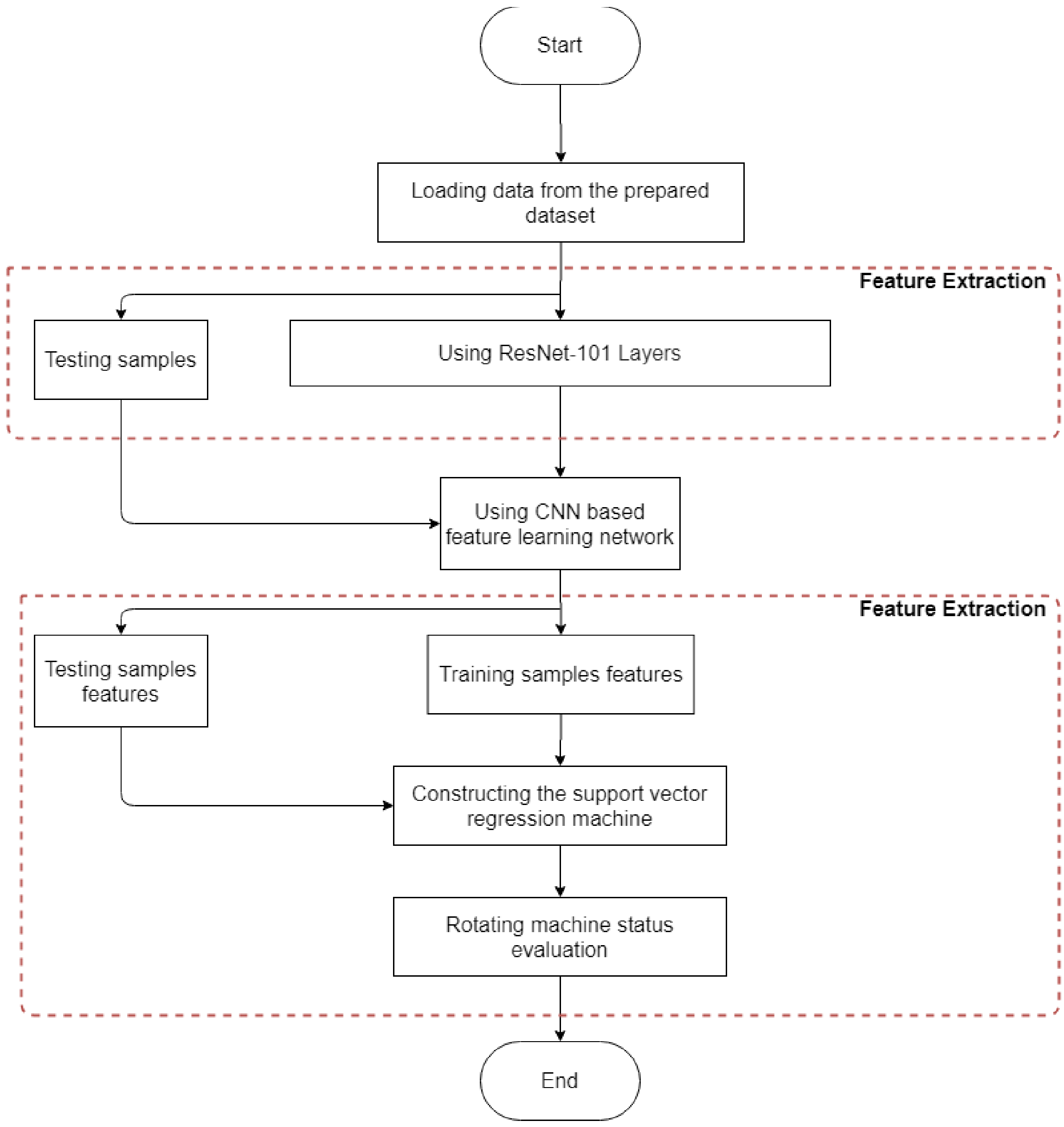


Fig. 5. The process of training and testing of Cona Detect proposed model.

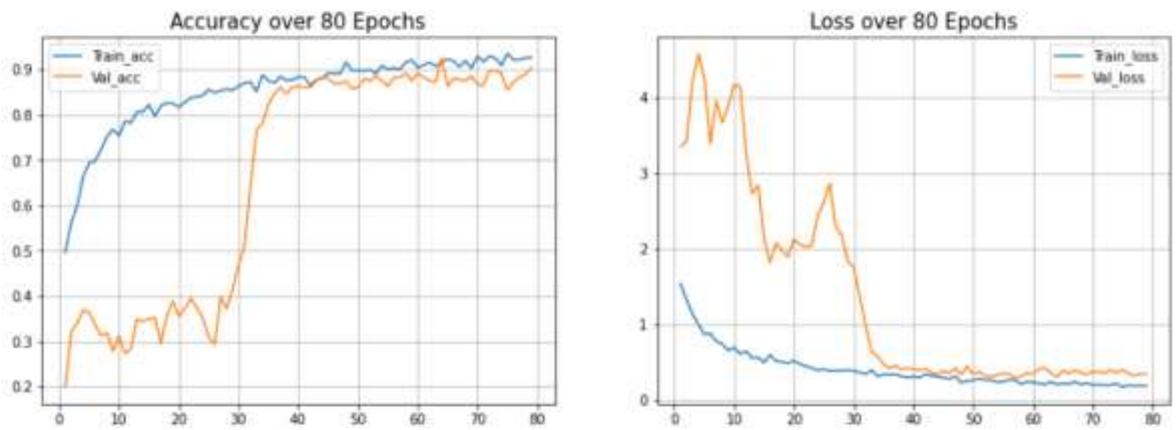


Fig. 6. The accuracy and loss graph over 80 Epochs when running 4 folds using ResNet101 architecture.

TABLE II. CONA DETECT LAYERS

Layer (type)	Output Shape	Param #
resnet101 (Functional)	(None, 4, 4, 2048)	42658176
flatten (Flatten)	(None, 32768)	0
dropout (Dropout)	(None, 32768)	0
dense (Dense)	(None, 256)	8388864
dense_1 (Dense)	(None, 4)	1028

Total params: 51, 048, 068
Trainable params: 50, 942, 724
Non-trainable params: 105, 344

B. Experimental method and results

The process of the proposed model will follow these instructions: Recognizing an individual with COVID-19 from an X-ray of the chest image. One way to do this is to match pre-selected lung symptoms from the imaging and a lung database. First of all, use algorithm ResNet101 to examine the features [14]. From there the algorithms select the information, and these features are then used to search for other images with matching features. The training is followed by creating a correct model answering our questions accurately in most situations. After training the algorithm, test its effectiveness, and repeat it many times. Using testing data, this data has the same structure as the training data, but it will be the dataset being not included in the training data set. Test each sample of test data, and test the operational model as a whole. End the process after finishing.

The proposed model, Cona Detect was executed in Keras on top of Tensorflow 2.0 [15], [16]. The model was used to teach on an adjusted dataset using Adam optimizer with a learning rate of 0.00001, batch size of 32, and epoch value of 80 [17]. All the analyses and training were done on Google Colaboratory Windows server [18]. We used a 4-fold cross-validation approach to evaluate the production of our main 4-class model [19]. The training set was randomly separated into 4 equal sets. Three out of four sets were used to train the CNN model while the remaining set was used for validation. This strategy was repeated 4 times by shifting the validation and training sets. The final execution of the model was recorded by averaging values obtained from each fold. The process of the Cona Detect proposed model is demonstrated in Fig. 5. Plots of accuracy and loss on the training and validation sets over training epochs for Fold 4 are displayed in Fig. 6.

To evaluate, the model must give out the value of accuracy, precision, recall and F-measure when training and testing the dataset [20].

The accuracy is the result of the total number of images correctly classified divided by the total number of images in the dataset that have been used for testing.

The precision is the result of the sum of all True Positives divided by the sum of all True Positives added with False Positives.

The recall is the result of the sum of all True Positives divided by the sum of all True Positives added with False Negatives.

The F-measure is the result of the multiplication of 2 versus Precision versus Recall and divided by sum of all Precision and Recall.

These formula is given below:

$$Accuracy = \frac{Number\ of\ images\ correctly\ classified}{Total\ number\ of\ images} \quad (1)$$

$$Precision = \frac{Sum\ of\ all\ TP}{Sum\ of\ all\ TP + Sum\ of\ all\ FP} \quad (2)$$

$$Recall = \frac{Sum\ of\ all\ TP}{Sum\ of\ all\ TP + Sum\ of\ all\ FN} \quad (3)$$

$$F - measure = \frac{2 * Precision * Recall}{Precision + Recall} \quad (4)$$

The Cona Detect layer is displayed is Table II, which shows the layer type that has been used in the proposed model, as well as the number of parameters that have been trained.

After training and testing, the value of overall accuracy, precision, recall and F-measure computed for each fold by formulae given in *(1)*, *(2)*, *(3)*, *(4)* are summarized in Table III.

TABLE III. RESULTS OF 4-FOLDS TRAINING AND TESTING

folds	precision	recall	f1-score	support
0	0.95	1.00	0.97	35
1	0.96	0.98	0.97	100
2	0.87	0.87	0.87	75
3	0.88	0.83	0.85	70
accuracy			0.91	280

Finally, the proposed model will give out the confusion matrix to show the correlation between all of the classes have just been training and testing. The confusion matrix of Cona Detect proposed model (with 4-folds and 4 classes) is illustrated in Fig. 7.

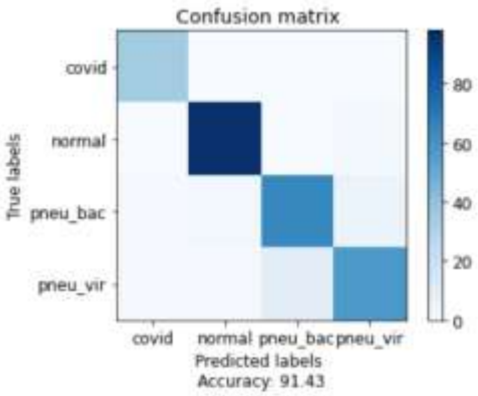
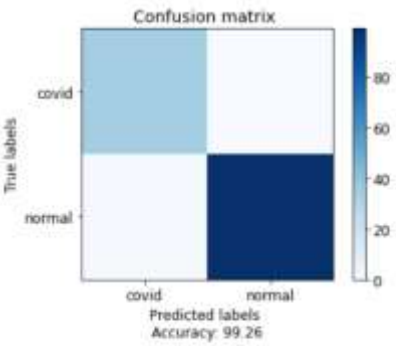
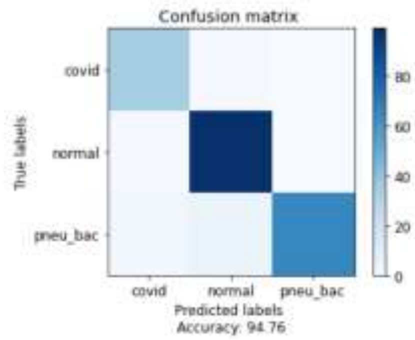


Fig. 7. The confusion matrix with 4 classes using Cona Detect proposed model (ResNet101).

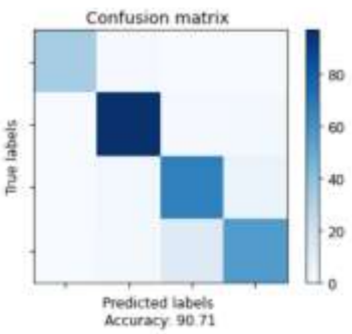


a) 2 classes

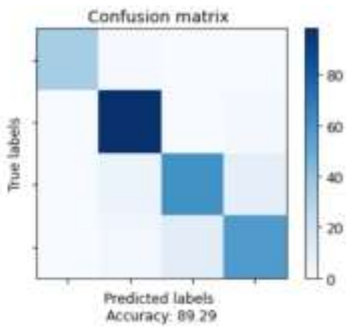


b) 3 classes

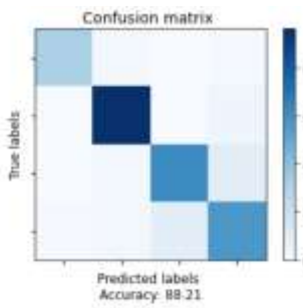
Fig. 8. The confusion matrix using Cona Detect proposed model (ResNet101) (a) 2 classes (b) 3 classes



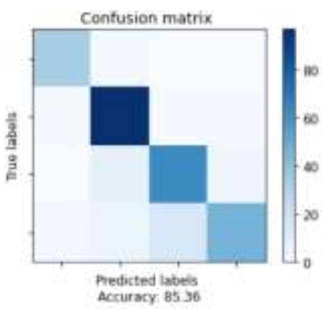
a) VGG16



b) VGG19



c) ResNet50



d) Xception

Fig. 9. The confusion matrix with other CNN models (a) VGG16 (b) VGG19 (c) ResNet50 (d) Xception.

As we can see from Fig. 7 and Fig. 8, the result of the Cona Detect proposed model is 91.43% when running with 4 classes. With 3 classes, the result would be 94.76% and with only 2 classes, the proposed model gives out a really high percentage of correct validation, 99.26%.

TABLE IV. COMPARED RESNET101 WITH OTHERS

CNN Models	Accuracy	Loss
VGG16	90.71%	0.436
VGG19	89.29%	0.504
ResNet50	88.21%	0.369
Xception	85.36%	0.455
ResNet101	**91.43%**	**0.343**

Comparing to others CNN models (VGG16, VGG19, ResNet50, and Xception, using the same parameters and dataset), the result of ResNet101 of Cona Detect gave out a higher accuracy and lower loss. The result is shown in Table IV and the confusion matrix of those models is illustrated in Fig. 9.

IV. CONCLUSION

As the number of positive cases of COVID-19 pandemic is rising unexpectedly day by day, many nations are suffering from a lack of resources, including testing kits and masks for protection. Not even a single positive case must go unidentified during this health emergency. With this worldwide difficulty, we proposed a deep learning approach to identify COVID-19 patients from their chest X-ray images. The proposed method (Cona Detect) is a CNN model designed to recognize COVID-19 cases using chest X-ray images as the training dataset. The model has been trained and tested on a dataset prepared by getting chest X-ray images of many pneumonia as well as COVID-19 cases from various openly accessible databases. Cona Detect is computationally less costly and reached encouraging results on the prepared dataset. Using ResNet101 as the CNN model, it reaches the accuracy of 91.43%, higher than compared to other CNN models. The performance can more be improved once more training data becomes available. Cona Detect still needs study and testing but with higher accuracy for COVID-19 cases, Cona Detect can still be advantageous for radiologists and health experts to obtain deeper recognition into important aspects correlated with COVID-19 cases. Cona Detect hopes to make a great combination with other testing traditional methods to help countries all around the world get over with the pandemic.

REFERENCES

[1] World Health Organization. Novel Coronavirus (2019-nCov). https://www.who.int/docs/default-source/coronaviruse/situation-reports/20200121-sitrep-1-2019-ncov.pdf?sfvrsn=20a99c10_4&fbclid=IwAR20jLTU0Dqjw7jGTauTaiRrypchDeRwLUg7_cc2tXSc8MU-IwQcNoYqLCw

[2] World Health Organization. Naming the coronavirus disease (COVID-19) and the virus that causes it. https://www.who.int/emergencies/diseases/novel-coronavirus-2019/technical-guidance/naming-the-coronavirus-disease-(covid-2019)-and-the-virus-that-causes-it

[3] World Health Organization. Archived: WHO Timeline - COVID-19. https://www.who.int/news-room/detail/27-04-2020-who-timeline---covid-19

[4] Worldometer. Coronavirus Update (Live). https://www.worldometers.info/coronavirus/?

[5] World Health Organization. Q&A on coronaviruses (COVID-19). https://www.who.int/emergencies/diseases/novel-coronavirus-2019/question-and-answers-hub/q-a-detail/q-a-coronaviruses#:~:text=symptoms

[6] ScienceDirect. Diagnosis of the Coronavirus disease (COVID-19): rRT-PCR or CT? https://www.sciencedirect.com/science/article/pii/S0720048X20301509

[7] American Journal of Roentgenology. Coronavirus Disease 2019 (COVID-19): Role of Chest CT in Diagnosis and Management. https://www.ajronline.org/doi/10.2214/AJR.20.22954

[8] World Health Organization. Global research on coronavirus disease (COVID-19). https://www.who.int/emergencies/diseases/novel-coronavirus-2019/global-research-on-novel-coronavirus-2019-ncov

[9] Markus Schmitt. How to fight COVID-19 with machine learning. https://www.datarevenue.com/en-blog/machine-learning-covid-19

[10] The Research Nest. Deep Learning Models For Medical Image Analysis And Processing. https://medium.com/the-research-nest/deep-learning-models-for-medical-image-analysis-and-processing-a4f8ba58e58f

[11] Ian H. Witten, Christopher J.Pal. Deep Neural Network. https://www.sciencedirect.com/topics/computer-science/deep-neural-network

[12] Walter Hugo Lopez Pinaya, Sandra Vieira, Rafael Garcia-Dias, Andrea Mechelli. Convolutional neural networks. https://www.sciencedirect.com/science/article/pii/B9780128157398000109?fbclid=IwAR1ce1yhcRc32SV8bN5dlHCC7du3HoeiVV-uLg25zA2wGrJHAHDds_jJFjs

[13] Sik-Ho Tsang. Review: ResNet — Winner of ILSVRC 2015 (Image Classification, Localization, Detection). https://towardsdatascience.com/review-resnet-winner-of-ilsvrc-2015-image-classification-localization-detection-e39402bfa5d8

[14] Prakash Jay. Understanding and Implementing Architectures of ResNet and ResNeXt for state-of-the-art Image Classification: From Microsoft to Facebook [Part 1]. https://medium.com/@14prakash/understanding-and-implementing-architectures-of-resnet-and-resnext-for-state-of-the-art-image-cf51669e1624

[15] Keras. Developer guides. https://keras.io/guides/

[16] TensorFlow. Effective TensorFlow 2. https://www.tensorflow.org/guide/effective_tf2?hl=en

[17] TensorFlow. tf.compat.v1.train.AdamOptimizer. https://www.tensorflow.org/api_docs/python/tf/compat/v1/train/AdamOptimizer

[18] Google Colaboratory. Welcome to Colaboratory. https://colab.research.google.com/notebooks/intro.ipynb?hl=en

[19] Jason Brownlee. A Gentle Introduction to k-fold Cross-Validation. https://machinelearningmastery.com/k-fold-cross-validation/

[20] Renuka Joshi. Accuracy, Precision, Recall & F1 Score: Interpretation of Performance Measures. https://blog.exsilio.com/all/accuracy-precision-recall-f1-score-interpretation-of-performance-measures/