Pneumonia and COVID-19 Detection using Convolutional Neural Networks

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***Abstract*— COVID-19 also known as Severe Acute Respiratory Syndrome Corona virus-2 is a contagious disease that is released from tiny droplets containing saliva or mucus from respiratory system of a diseased person who talks, sneeze, or cough. It spreads rapidly through close contact with somebody who is infected or tapping or holding a virus contaminated objects and surfaces. Another infectious illness known as Pneumonia is often caused by infection due to a bacterium in the alveoli of lungs. When an infected tissue of the lungs has inflammation, it builds-up pus in it. To find out if the patient has these diseases, experts conduct physical exams and diagnose their patients through Chest X-ray, ultrasound, or biopsy of lungs. Misdiagnosis, inaccurate treatment, and if the disease is ignored will lead to the patient's loss of life. The progression of Deep Learning contributes to aid in the decision-making process of experts to diagnose patients with these diseases. The study employs a flexible and efficient approach of deep learning applying the model of CNN in predicting and detecting a patient unaffected and affected with the disease employing a chest X-ray image. The study utilized a collected dataset of 20,000 images using a 224x224 image resolution with 32 batch size is applied to prove the performance of the CNN model being trained. The trained-model produced an accuracy rate of 95% during the performance training. Based on the result of testing conducted, the research study can detect and predict COVID-19, bacterial, and viral-pneumonia diseases based on chest X-ray images.**

Keywords— Pneumonia Detection, COVID-19 Detection, Deep Learning, VGG-16, Convolutional Neural Networks

I. INTRODUCTION

Corona-virus or COVID-19 was confirmed by the World Health Organization a crisis on global health or pandemic considering the scope of its span on a global scale and a highly contagious disease [1]. The government in different countries has imposed stringent precautionary actions to combat the coverage and intensity of spreading of the virus like flight-restrictions, physical-distancing, border-restrictions, and practicing good personal hygiene. The corona-virus can be contaminated through breathing droplets released by a person who is chatting, sneezing, or coughing [2]. It spreads rapidly when there is close interaction with the infected person or by affecting infected surfaces and objects [3]. The best way to protect a person from a virus is by avoiding being exposed since until now there is no vaccine to combat the COVID-19 [3]. However, there are on-going researches and trials for potential treatment being conducted by scientists as of today [4]. More than 18 million infected cases of COVID-19 around 213 countries around the world [1]. It also claimed almost 700 thousand fatalities and around 12 million recoveries as of August 2020 [1].

Pneumonia can be a life-threatening illness if not diagnose properly and can result in the death of a person associated with this kind of ailment [5]. It is in a form of severe respiratory illness caused by transmittable agents like viruses, or bacteria that affects the lungs [5]. It can be spread through the nose or throat and affect the lungs if they are inhaled or communicated through air-borne droplets from a person coughing or sneezing [6]. The lungs of a person are made up of small sacs or alveoli that supplies the air passage whenever a well fit person breathes [5]. When a person is infected with pneumonia, it limits the oxygen intake and makes breathing difficult and painful due to tissue soreness caused by alveoli covered with fluids or pus [6]. An aging person from 50 years of age and above and kids under five years of age are susceptible to pneumonia illness for they have a weaker immune system and it has taken over a million lives globally [5]. In the Philippines, it has reported nearly 58,000 mortalities in 2016 and the 3rd top killer behind heart diseases and cancer.

COVID-19 signs and indications are almost identical to the pneumonia, if not properly diagnose will lead to incorrect diagnosis now that many hospitals around the world are congested. Many of these hospitals are working 24/7 due to massive increase of infections and most of its medical personnel are also infected with the virus [4]. Imprecise findings of pneumonia or non-COVID-19 may be labeled incorrectly as COVID-19 infected and setbacks in proper treatment are costly, the struggle and risk of being exposed to other positive patients of COVID-19.

Infected patients require an instantaneous medical response and efficient examination to stop the further wide-spreading of COVID-19. The utmost method in the clinical examination for COVID-19 patients is Reverse Transcription-Polymerase Chain Reaction (RT-PCR) that employs respiratory-specimen samples for testing [7] and reference as the basic method for detection. Nevertheless, this procedure is conducted manually, difficult and timewasting process with an accuracy rate of 63% only [7]. Besides, there is a deficiency in RT-PCR supply kits for its demand in the market and hinders the efforts in the prevention of the disease [6]. Other methods in diagnosing COVID-19 includes laboratory analysis, epidemiological history, Chest Radiograph or CXR, and pathogenic testing. Bronco-pneumonia which triggers fever, coughing, dyspnea, and respiratory failure is one of the characteristics of severe COVID-19 infection [8-9]. Radiological imaging that is easily available in most hospitals is one significant diagnostic instrument for COVID-19. The radiologist captures a chest image of the patient through a radiograph instrument. A radiograph image is generated through radiation on a thin-skinned film to validate patients infected with disease or not-infected. Even though usual CXR images could assist early signs of suspected cases, the images of various related viral-pneumonia are similar, and they interrelate with other contagious lung illnesses. Hence, for a radiologist, it is not easy to distinguish COVID-19 to other related viral-pneumonia.

Convolutional Neural Networks (CNNs) have shown to be tremendously valuable in feature-extraction and learning through training and for that reason, it is commonly implemented in medical researches [5-6]. The application of CNN has improved the image attributes in the environment with low-light conditions, efficient endoscopy video, lung nodule detection and identification thru computed tomography images, analysis of pediatric-pneumonia through X-ray image of chest, and other pulmonary related studies. Methods of Deep learning covering the deep CNNs techniques on X-Ray images of chest are receiving recognition and encouraging outcomes has made it known in diverse applications.

II. Related works

Since the few decades, computer-aided diagnostic (CAD) for medical imaging has been used. Beginning from a conventional way to artificial intelligence method and from machine learning to deep learning approach, this due to the high-performance result [6]. Several techniques have been applied for classifying diseases like cancer, skin illnesses, chest diseases, and many others. Deep convolutional neural networks (DCNN) with increased dataset collections are the most used methods for classifying numerous types of medical images with its high-accuracy result.

A. Deep Learning (DL)

Learning in a DL approach is a process of developing behavior based on the learned features or its experience [10]. DL is a sub-field of artificial-intelligence and machine-learning which improves its utilization found on the performance of different applications of artificial-intelligence and machine-learning [5]. Deep learning affects the acceleration of GPU-based computing power and non-linearity that allows deeper networks for improved operation [11].

Progressive researches in deep learning algorithm have increased rapidly and the resemblance of this was the diagnosis of pneumonia in the medical area is a wide-known discipline. A study for identification is done by applying image processing techniques. Algorithms developed cropped and extract the image of the lung region. It uses Otsu-thresholding to segregate the healthy part of the lungs from the disease-infected part of the lungs. Sharma et al. investigated this approach that will help them assist in diagnosing patients in their study [12]. The study of S. V. Militante and B. G. Sibbaluca trained 5 different deep learning models and compared each model the best model to detect pneumonia and healthy chest X-ray images using 26,684 datasets. The result

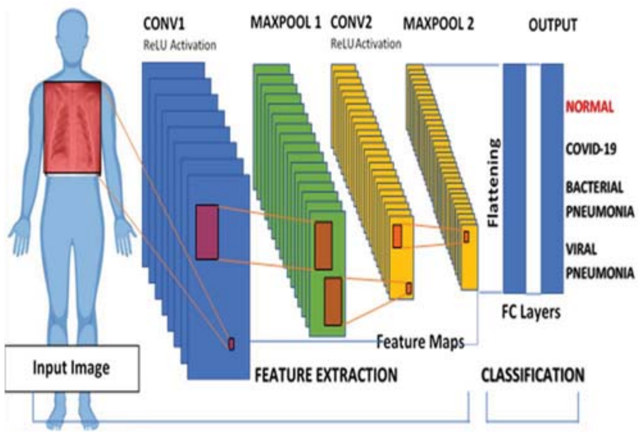

Fig.1. CNN Process Model.

of their study obtained an accuracy rate of 97% with the best model the VGG-Net model to detect pneumonia [6].

B. Convolutional Neural Networks

Stimulated primarily by the human-brain, the convolutional neural network is a feed-forward neural network capable of classification and feature extraction process. CNN links 4 key layers: the convolutional layer, the rectified linear unit (ReLU) activation layer, subsampling layer, and fully-connected layer [13]. The CNN process model is shown in figure 1. A standard convolutional layer usually takes an input image and with the help of the kernel creates a feature map [14]. Each neuron stores several inputs from the convolutional layer and several connections of neuron connection overlap each other to improve the representation of input images. The reduced number of parameters is the result form sharing of weights and every convolutional layer that connects to a ReLU activation layer offers the CNN additional acceleration for more complex functions [15]. At times there is a possibility of overfitting in CNN, so the Pooling is applied a sub-sampling process that overpowers overfitting and lowers the number of parameters [14]. Lastly, fully connected layers with one or more numbers are complemented to encapsulate the trained-features to determine the categorized result. In this paper manuscript, the authors propose deep learning for classifying chest diseases like pneumonia and COVID-19. The paper allows showing the wide ability of CNN.

III. Methodology

Deep CNNs indeed achieve better performance using a large dataset compared to a smaller one. Granting there are a significant number of infected COVID-19 patients globally, but the number of publicly available chest X-ray images on-line are insignificant and dispersed. Hence, the authors in this work have described a reasonably large dataset of COVID-19 infected chest X-ray images [16] although normal and pneumonia images are promptly accessible publicly [17] and applied in this study.

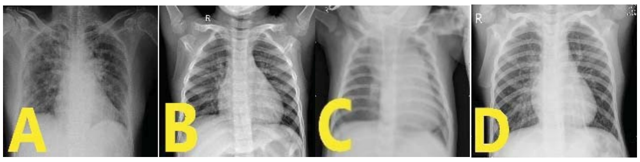

Fig.2. Sample X-ray images from the dataset: COVID-19 infected (A), Normal (B), Bacterial-Pneumonia (C), and Viral-Pneumonia (D).

A. Dataset Collection

Analysis of Chest X-Ray is one difficult undertaking to consider in a health discipline. Presently, there are thousands readily available datasets for chest X-Ray and these datasets are only constrained on a few thousand images. Radiology Society of North America (RSNA) back in 2018 organized a pneumonia detection challenge from the images of chest X-ray using artificial intelligence (AI) [17]. It requires the participants to develop an algorithm that will detect and identify pneumonia through chest x-ray images. In this database, a normal chest X-ray with no-lung infection and non-COVID pneumonia images were available [18].

Kaggle chest X-ray database is an incredibly popular database containing 15,798 chest X-ray images of normal or healthy, viral, and bacterial-pneumonia ranging from 800 pixels to 1900 pixels resolution [18]. For the total of 15,798 image datasets, 5,396 images are affected by bacterial pneumonia and 4,865 images with viral pneumonia, and 5,537 images are from normal or healthy chest X-rays. Positive and suspected COVID-19 images were acquired in publicly available sources [16]. Chest X-ray images for normal and affected with pneumonia were utilized from this collection to generate the latest database collection. Illustrated in figure 2 exhibits the images from the database collection of images of chest X-rays for normal X-ray, COVID-19 infected, bacterial, and viral-pneumonia.

B. Proposed CNN Architecture

The CNN is constructed with numerous smaller units termed nodes/neurons which are arranged in the layered-architecture. These nodes comprise of weights that during the training of the model are updated using optimizing techniques like backpropagation etc. Every single CNN model is consists of the convolutional or feature extraction portion and the classification portion. The components and structure of the VGG-16 CNN model applied are described in Table I.

1) Convolutional Layer: This layer forms a basic building block for convolutional neural networks. This layer uses a fixed-size filter to extract several features. The inspection of images is done by transferring the filters per strides, in this case, there are 6 convolutional layers with the size of 32, 64, 64, 128, 128, 128 filters in the CNN model. Every layer uses 2D convolutional filters with a size of 3x3 and a stride of one.

2) Batch Normalization: It is used to improved the learning rate of the CNN model and this layer standardizes the input image. Batch normalization in a CNN model is applied after each convolutional-layer.

3) Pooling Layer: Pooling is a method that downsamples the collected feature-map from a convolutional layer. Max-pooling and average-pooling are usually used and in every convolutional layer, a max-pooling with pooling filter-size of 2*2 is utilized.

TABLE I. VGG-16 CNN MODEL ARCHITECTURE

Layer (type)	*Output Shape*	*Param #*
Input	(224, 224, 3)	0
Convolution	(224, 224, 32)	896
Batch Normalization	(224, 224, 32)	128
Activation	(224, 224, 32)	0
Max Pooling	(112, 112, 32)	0
Convolution	(112, 112, 64)	18496
Batch Normalization	(112, 112, 64)	256
Activation	(112, 112, 64)	0
Max Pooling	(112, 112, 32)	0
Convolution	(112, 112,64)	36928
Batch Normalization	(112, 112, 64)	256
Activation	(112, 112, 64)	0
Max Pooling	(56, 56, 64)	0
Convolution	(56, 56, 128)	73856
Batch Normalization	(56, 56, 128)	512
Activation	(56, 56, 128)	0
Max Pooling	(56, 56, 64)	0
Convolution	(56, 56, 128)	147584
Batch Normalization	(56, 56, 128)	512
Activation	(56, 56, 128)	0
Flatten	100352	0
Dense	512	51380736
Batch Normalization	512	2048
Activation	512	0
Dropout	512	0
Dense	2	1026
Activation	2	0

4) Activation: This function is a non-linear transformation of inputs that are applied at each end of a layer. ReLU or Rectified Linear Unit is a common activation function that is applied at each end of the layer and in the final layer, there are two nodes used with an activation function.

5) Dropout: A technique applied to reduce the overfitting of the model. Certain nodes in the layer using the dropout method are randomly selected to be inactive on some occasions. This will prevent the model from getting excessively familiar with the data. The dropout of 0.5 was employed in the dense layers of the model for classification.

6) Dense Layers: The output of the convolutional-layer is further flattened and submitted as input to the dense-layer. The convolutional-layer task is to extract features and the role of the dense layer is for the classification of images. The CNN architecture has two dense-layers with 512-nodes each and 2 nodes for the final layer.

IV. EXPERIMENTAL RESULT

The entire application was performed in 64-bit Windows10 Operating System using Python 3.6 version as the software development language. The entire experiment was coded in the Tensorflow framework to develop and train the model using Keras as the backend. The machine with

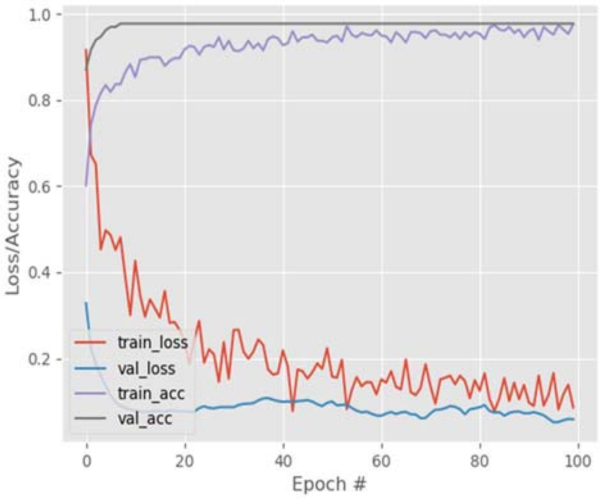

Fig. 3. Training performance end-result using the VGG-16 model.

TABLE II. ASSESSMENT OF VGG-16 CNN MODEL HAVING A BATCH SIZE OF 32 AND EPOCHS OF 100

Criterion	Normal	COVID-19	Pneumonia Bacterial	Pneumonia Viral
Precision	1.00	0.95	0.97	0.94
Recall	0.94	1.00	0.94	0.97
F1-Score	0.95	0.95	0.94	0.92

Intel® Core™ i7-8700 CPU @4.60GHz with 12M Cache, 16GB RAM is used for implementing the model. Data augmentation was also integrated during the conduct of experiments to increase the image dataset. Some of the methods applied are image-flipping, image-rotation, zoom-range, and shift-range. Optimizer forms and shapes the model into the utmost accurate achievable form by futzing with the weights. In the study, a learning rate of 0.0001 utilizing the Adam optimizer and a cross-entropy using categorical were adopted as optimization features. A batch size of 32 and an epoch of 100 as shown in Table II the matrix result of the assessment of the VGG-16 CNN model. The diagrams of validation-accuracy compared to accuracy and validation-loss compared to training- loss are displayed in figure 3. It shows the overall performance of the model that runs in a repeatitive steps to extract-features from the image during model-training presented in a plot. The result produced a 95% accuracy as illustrated in Table II. The testing of Chest X-ray images is illustrated in figure 4 to figure 7. The sample result of Chest X-ray image is displayed in figures 4(A) and 4(B) having a prediction result of Normal Chest X-ray with an accuracy rate of 97.83% and 95.30%. A COVID-19 infected sample result of an image is illustrated in figures 5(A) and 5(B) has an accuracy rate of 99.94% and 98.50%. Figures 6(A) and 6(B) illustrates a sample image of Pneumonia with bacterial infection with an accuracy rate of 93.29% and 87.15% and figures 7(A) and 7(B) displays a sample Chest X-ray image infected with Pneumonia-viral infected with an accuracy rate of 90.99% and 92.61% respectively. The trained model attained an accuracy rate of 95% during the conduct of training.

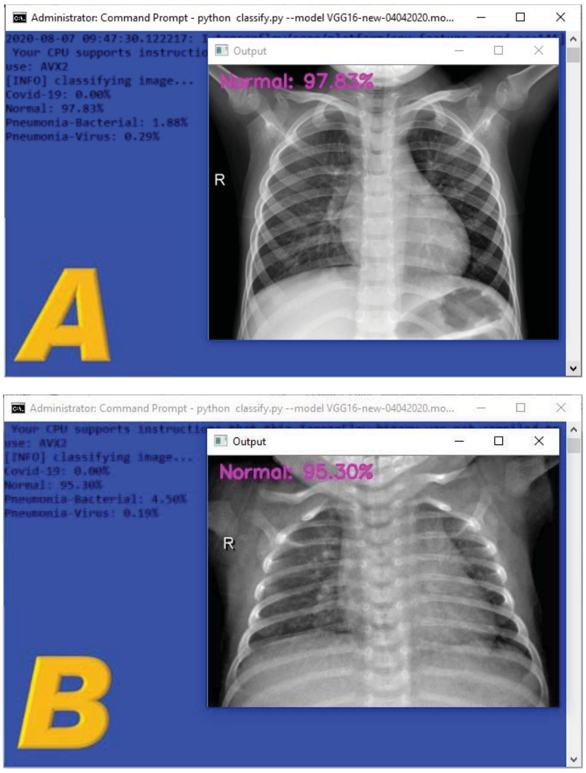

Fig. 4. Sample result of Chest X-ray image having a prediction of a Normal Chest with a precision percentage of 97.83% (A) and 95.30% (B).

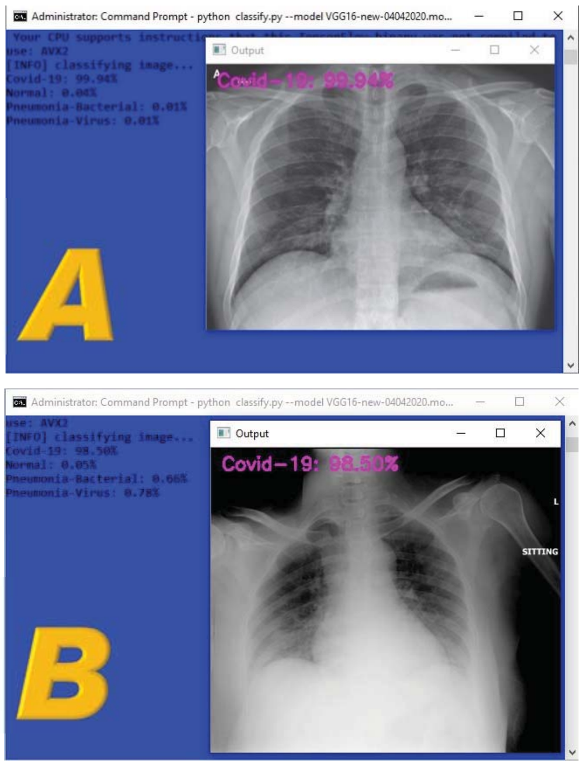

Fig. 5. Sample result of Chest X-ray image having a prediction of a COVID-19 infection with a precision percentage of 99.94% (A) and 98.50% (B).

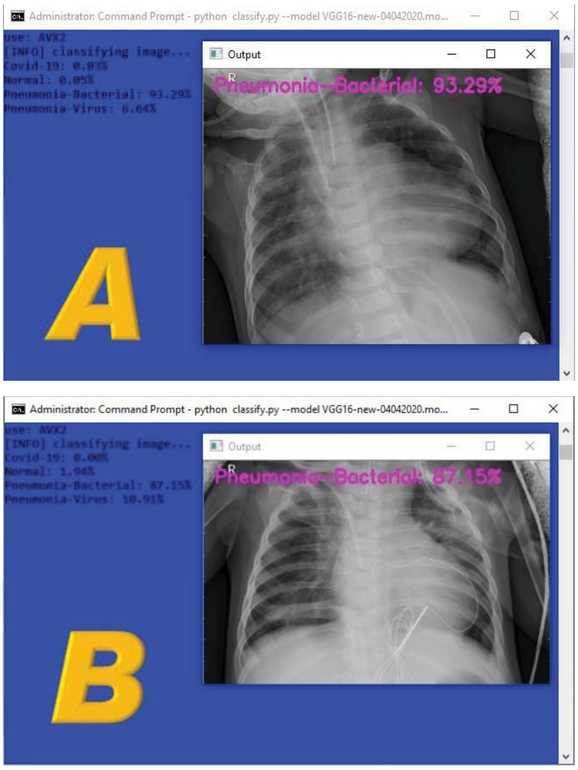

Fig. 6. Sample result of Chest X-ray image having a prediction of a Pneumonia-Bacterial infection with a precision percentage of 93.29% (A) and 87.15% (B).

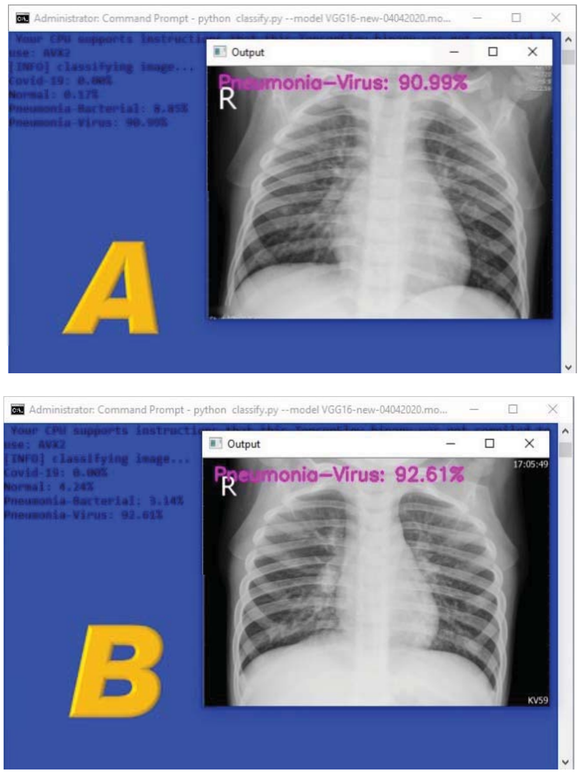

Fig. 7. Sample result of Chest X-ray image having a prediction of a Pneumonia Virus infection with a precision percentage of 90.99% (A) and 92.61% (B).

V. Conclusions and Recommendations

The trained VGG-16 model the researchers proposed in this research study for the COVID-19 detection and pneumonia detection on chest x-ray images using the CNN method have meaningful results. The developed CNN model was effective in extracting features from an x-ray image and forecast the occurrence or nonexistence of COVID-19, bacterial, and viral-pneumonia. Likewise, testing-data in the research was intensified through data augmentation techniques. In addition to the improvement of computer-related applications in the medical division, COVID-19 and pneumonia can be efficiently found employing chest radiographs with the support of CNN and deep learning technologies. Methodologies developed in the conduct of this research in which COVID-19, bacterial, and viral-pneumonia can be forecast with greater accuracy, and in this case our study obtained 95% accuracy. The medical field through automated diagnosis is the essential area that will gain precisely from this research. Future studies can make better a performance of CNN architecture by tuning the hyper-parameters and transfer learning combinations. Improved complex network-structure might likewise achievable to determine the best model for pneumonia and the COVID-19 detection system.

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