Detection of COVID-19 And Pneumonia from Chest X-Rays

Kevin Joji Mathews - B180880EC

***Abstract*— Most people who get Coronavirus Disease (COVID-19) have mild or moderate symptoms like fever, cough, and shortness of breath. However, those who catch the new coronavirus get severe pneumonia in both lungs. COVID-19 pneumonia may be a serious illness that will be deadly. One of the sensible examinations for COVID-19 and Pneumonia is chest radiography. Infected patients display abnormalities in chest X-ray images. A deep learning technique (transfer learning) can used in detecting abnormalities in the X-ray images, which could prove to be a potential solution to help diagnose the disease. This paper introduces a deep learning Convolutional Neural Network (CNN) that can detect COVID-19 and Pneumonia in chest radiographs. A large and diverse dataset which comprises around 6000 chest X-ray images is used to train the presented model and is used to accurately predict whether a patient is infected with COVID-19 or Pneumonia or is healthy. Two learning models have been proposed. The first model is a pre-trained model based on VGG19, and the second model is developed from scratch. The results indicate that the pre-trained model outperforms the model that was developed from scratch.**

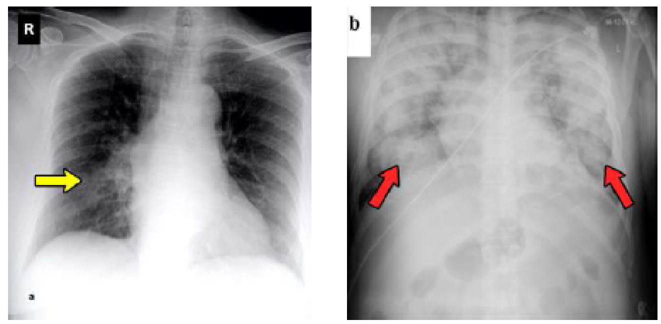
I. INTRODUCTION

The coronavirus disease (COVID-19) is a serious and contagion that has spread worldwide since December 2019. COVID-19 was first reported in Wuhan, China. After a month, due to its rapid spread rate, COVID-19 was declared as a public health emergency of international concern. The COVID-19 pandemic of September 2020 has resulted in over 33 million confirmed cases and over 1 million deaths worldwide.

Although the COVID-19 disease can cause multi-organ dysfunctions, results show that the lungs are the most affected organs of the human body. Whereas in the case of Pneumonia, the infected lungs' air sacs (alveoli) become inflamed and fill up with fluid or pus that makes it difficult to breathe. Hence, the lungs of the human body are taken as the focal point for COVID-19 and Pneumonia detection. Both the COVID-19 and Pneumonia share some common symptoms such as fever, cough, dyspnea, and fatigue, making it difficult to determine if the patient is either infected with COVID-19 or with Pneumonia.

When examining the chest X-rays of individuals with COVID-19 pneumonia, whiteness can be noticed in the lungs. The degree of the whiteness on chest X-rays usually indicates the severity of the condition. In the normal scenario, ground-glass opacity occurs, with the possibility of linear opacities (e.g., peripheral horizontal white lines), resulting in veiled lung markings as seen in figure 1a. It should be noted that in severe situations, due to the intense whiteness, the lung marks become undetectable, a phenomenon known as consolidation, as seen in figure 1b.

As a result, chest radiography, alone or in combination with laboratory and clinical examination, is frequently an effective technique for determining the first and correct diagnosis of COVID-19 pneumonia.



(a) Ground glass opacity (yellow arrow)

(b) Consolidation (red arrows)

Fig. 1: Whiteness in the lungs due to COVID-19 Pneumonia

This research presents a COVID-19 and Pneumonia classification system that was trained using transfer learning on two models (pre-trained and from scratch), as well as analysis on their efficiency, is done. The proposed models will be assessed based on their ability to detect COVID-19 and Pneumonia traces in X-ray images of the patients' chests.

The remaining part of the paper discusses the following. The proposed method's technique is discussed in Section 2. The two models that were employed are presented in Section 3. The experimental results obtained from the proposed models are discussed in Section 4. Section 5 brings the paper to a close with a general summary of the findings.

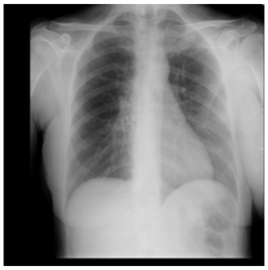
II. PROPOSED METHODOLOGY

This section describes the dataset used and explains the two deep learning models along with the transfer learning architecture.

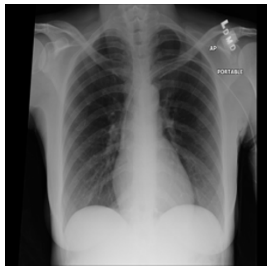
A. Dataset Description and Image Generation

Frontal view chest X-ray images from Normal, Pneumonia and COVID-19 cases are used in this study. The data was taken from the Kaggle dataset Chest X-Ray (Pneumonia, COVID-19, Tuberculosis). Because the number of X-ray samples for COVID-19 is somewhat low in comparison to the other two cases, images for COVID-19 are obtained using a second dataset (the COVID-19 Radiography Database from Kaggle). The dataset employed in this study comprises of 7326 chest X-ray images separated into three classes (1470 COVID-19 samples, 1583 Normal samples, and 4273

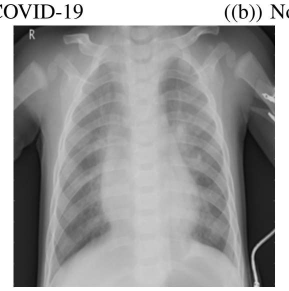
Pneumonia samples) (test, validation, train). The train folder contains 6401 images, the validation folder has 26 images, and the test folder has 899 images. An example of the dataset for COVID-19, Pneumonia, and Normal is shown in Figure 2.



((a)) COVID-19



((b)) Normal



((c)) Pneumonia

Fig. 2: Frontal-view chest X-Ray images from the dataset

Some preprocessing steps are then applied to the images before training the model. The images are reshaped to 150x150. To train the model, the images are divided into three classes, COVID-19, Normal, and Pneumonia, with class indices as 0, 1, and 2 respectively.

B. Transfer Learning

Transfer learning is one of the frequently used techniques in deep learning. It allows us to train models with small datasets in less time. The concept of transfer learning is based on the reality that knowledge obtained from one problem can frequently be used to a related problem. For example, the knowledge learned when learning to detect vehicles can be applied to detect trucks. When the many tasks are relatively connected, transfer learning is successful.

Transfer learning is beneficial when it involves medical data like images due to its limited availability. With the use of transfer learning on deep learning models, training can be performed on small datasets without any problem of overfitting.

In this paper, transfer learning has been applied on two models. A pre-trained network, such as the VGG19 trained on ImageNet, and transfer their knowledge onto our classification problem. And a model that is developed from scratch. Details about the proposed models are discussed in the next section.

III. Network Architecture

Under this section, two models are presented: a pre-trained VGG19 model and a model trained from scratch.

A. Pre-Trained Deep Learning Model

VGG19, a well-known deep learning model is chosen as a classifier, available in the TensorFlow library. This model is taken as the base model and a new untrained head is applied to it.

The VGG19 is a Convolutional Neural Network (CNN) architecture consisting of two convolutional filter layers (3x3) and one pooling layer repeated two times. Then, four convolutional filter layers (3x3) and one pooling layer were repeated three times. Finally, there are two fully connected layers and a softmax output. Figure 3 illustrates the network architecture of the VGG19 model.

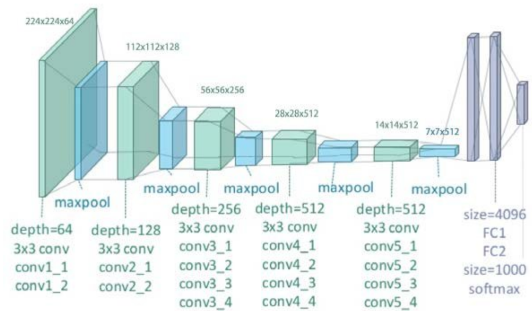


Fig. 3: Network architecture of VGG19

To fit the new classification problem, the final layers of the pre-trained network are removed and is replaced with new layers. The new layer begins with a 0.2 dropout layer, a flatten, and two fully connected networks of dimensions 128 and 64 respectively along with another 0.2 dropout layer. The final layer consists of three class heads (COVID-19, Normal, and Pneumonia) with a categorical cross-entropy loss function.

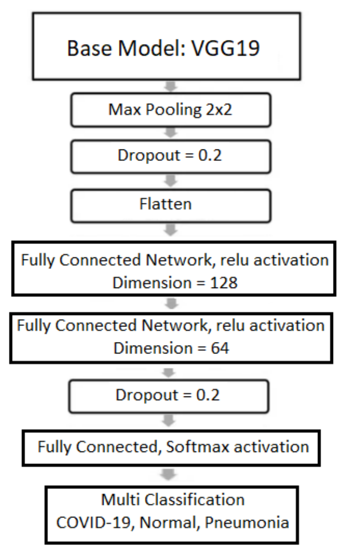


Fig. 4: Final architecture of the pre-trained model

B. Model Built from Scratch

This network was built in a similar fashion. It was built sequentially with three repetitions of convolutional and pooling layers, then a 0.2 dropout layer. Another convolutional and pooling layer along with flattening. Every convolutional layer has a kernel size of (3, 3). Finally, there are two fully connected layers of dimensions 128 and 64 respectively, that are relu activated, with a 0.2 dropout layer in between, and a softmax output layer for the three class classification. Figure 5 shows the final architecture of the model built from scratch.

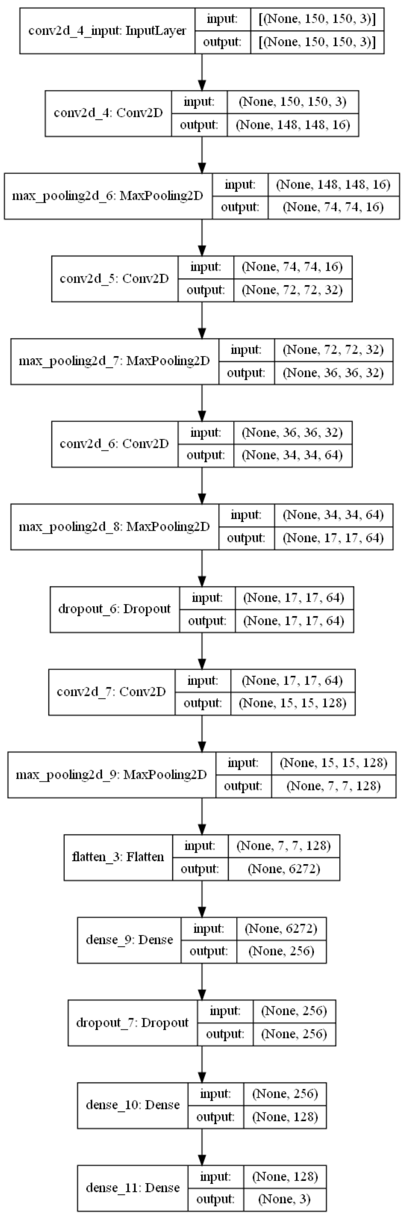


Fig. 5: Architecture of the model built from scratch

IV. Experimental Evaluation

A. Experimental Setup

The two deep models were developed in Python, using the TensorFlow library.

The CNN models were trained against the validation data using batches of size 8, for 30 epochs. An early stopping criterion, which monitors the validation loss, was set to 8 epochs in order to avoid overfitting.

Both the models were trained using Adam optimizer with default parameters, with a learning rate of 0.001. Lastly, the loss of the models was set to categorical cross-entropy (loss function used in multi-class classification tasks). The categorical cross-entropy loss function computes the loss by the following sum:

$$Loss = -\sum_{i=1}^{output size} y_i log(\hat{y_i}) \tag{1}$$

where $\hat{y_i}$ is the i^{th} scalar value in the model output, y_i is the corresponding target value, and output size denotes the number of scalar values in the model output.

B. Results

To test the proposed models, four performance metrics are considered,

- Prediction - measure of correctness of positive predictions
- Recall - ratio of total relevant instances correctly classified by the network
- Accuracy - proportion of correct predictions to the total predictions made by the classifier,
- F1 score - harmonic mean of precision and recall

	precision	recall	f1-score	support
COVID19	0.97	0.99	0.98	275
NORMAL	0.91	0.74	0.82	234
PNEUMONIA	0.87	0.96	0.92	390
accuracy			0.91	899
macro avg	0.92	0.90	0.90	899
weighted avg	0.91	0.91	0.91	899

Fig. 6: Classification report of pre-trained model

	precision	recall	f1-score	support
COVID19	0.94	0.95	0.94	275
NORMAL	0.93	0.41	0.57	234
PNEUMONIA	0.74	0.99	0.85	390
accuracy			0.82	899
macro avg	0.87	0.78	0.79	899
weighted avg	0.85	0.82	0.80	899

Fig. 7: Classification report of model built from scratch

Figure 6 and Figure 7 illustrates the classification report of the pre-trained model and model built from scratch respectively.

It can be observed that the pre-trained model (VGG19 pre-trained on ImageNet dataset) performed reasonably well with 91% precision and 90% recall in the classification task, whereas the model trained from scratch, had a precision of 87% and a recall of 78%. Now moving on to the accuracy and F1-scores of both the models, the pre-trained model achieved the highest score with 91% accuracy and 90% F1-score. The model trained from scratch obtained 82% accuracy and 79% F1-score.

Figure 8 shows the comparison between the accuracy and loss during training and validation stages for each epochs, on the pre-trained model, and Figure 9 shows the same for the model trained from scratch.

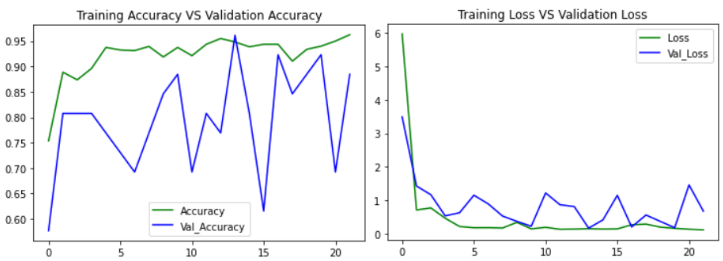


Fig. 8: Performance of pre-trained model

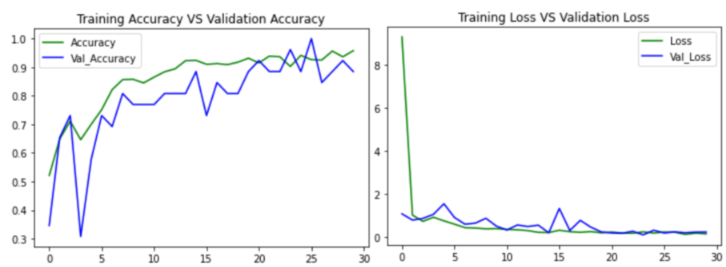


Fig. 9: Performance of model trained from scratch

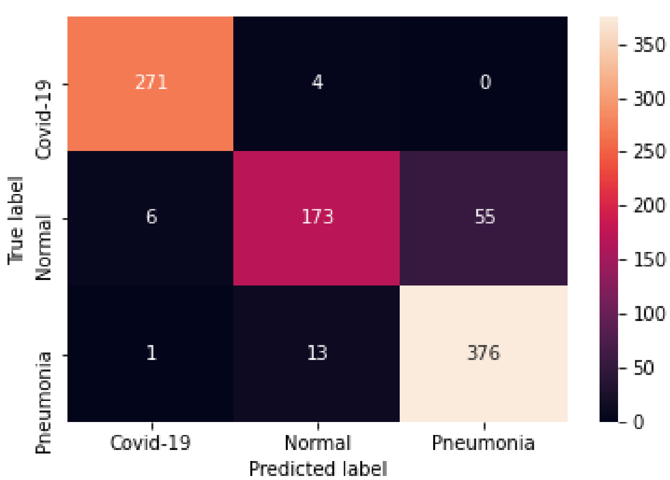


Fig. 10: Confusion matrix of pre-trained model

Figure 10 and Figure 11 denote the confusion matrix of the two models. From the above results, it is clear that the pre-trained model provides much better accuracy and performance when compared to the model trained from scratch for the dataset used.

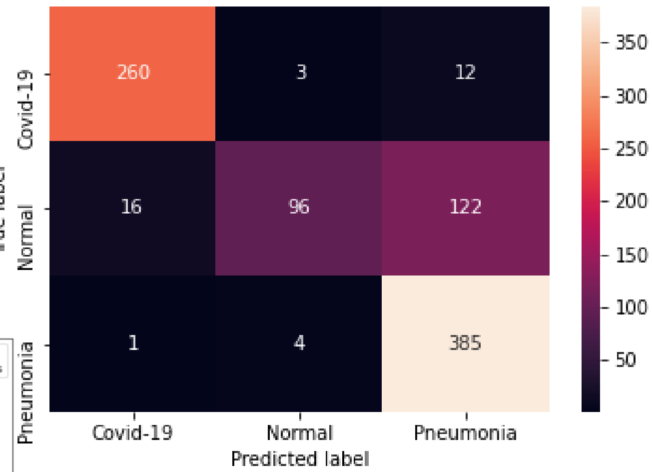


Fig. 11: Confusion matrix of model trained from scratch

V. CONCLUSIONS

In this paper, a three-class classification is performed on COVID-19 and Pneumonia using chest X-Rays. Two models were trained and tested to accurately categorize COVID-19 and Pneumonia chest X-Ray images. The results show that the VGG19 pre-trained model achieves significantly higher accuracy (91% accuracy) than the model trained from scratch (82% accuracy). The findings may aid in recognizing COVID-19 and Pneumonia from a chest X-ray at an earlier stage, allowing for a quicker decision to be made.

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