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Naïve method of identification of COVID-19 Infection using X-Ray Image

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Abstract – It is anticipated that severe pneumonia due to the COVID-19 would significantly impact medical services. Accurate diagnosis is crucial to reducing stress on the healthcare system. Imaging techniques such as chest X-rays and CT scans are often used to diagnose pneumonia. Despite CT scan being the gold standard, CXRs are still useful because they are more widespread, faster, and cheaper. This study aims to determine whether or not CXR images alone are sufficient for differentiating COVID-19 pneumonia from other types of pneumonia and healthy lungs. COVID-19, short for Novel Coronavirus Disease, is the name given to the virus that was identified late in 2019 in China and is considered exceedingly infectious. SARS-CoV-2 is a coronavirus, like many others, that may cause serious sickness. The sickness emerged in Wuhan, China, in December of 2019 and has since spread to more than 213 nations. People infected with COVID-19 often have a high body temperature, dry cough, and acute weariness. A multiclass and a hierarchical pneumonia classification were considered in developing our classification method. Because of the uneven data distribution in this region, we also suggested including resampling methods into the schema to re-balance the classes. Our results indicate that texture is one of the key visual elements of CXR photos, and our classification schema extracts features using a pre-trained CNN model and a set of well-known texture descriptors. We also explored early and late fusion techniques inside the schema to take advantage of the capabilities of many texture descriptors and base classifiers concurrently.

Keywords – COVID-19 Infection, X-Ray Image, COVIDX-Net, MobileNetV2, Xception, InceptionV3, ResNetV2, DenseNet121, VGG19

I. INTRODUCTION

Few in the contemporary period foresaw the outbreak of pneumonia produced by the coronavirus that causes severe acute respiratory syndrome (SARS CoV-2) or coronavirus illness 2019, which began at year's end (COVID-19). Medical professionals worldwide struggle to keep up with the fast global spread of the COVID-19 pandemic. The disease was first detected in Wuhan, China, but has now spread to every continent. Due to the time required for diagnosis and the high cost of test kits, deep learning and artificial intelligence research and apps have been developed to help doctors treat patients battling illnesses. There is a substantial obstacle to success presented by the high cost of diagnostic laboratory kits, especially in less developed countries. Using X-ray images for automatic detection might be helpful for hospitals and governments without access to a CT scanner or a laboratory kit for detecting COVID-19. A proper diagnosis is crucial since there is currently no effective therapy available. Deep learning approaches have been used for analyzing COVID-19 CXR images. In addition, we have classified the many studies in this field into three distinct groups: COVID-19 studies in the medical field, DL works in CAD connected to COVID-19, and CAD studies related to COVID-19 via deep transfer learning. The results, proposed procedures, datasets, data preparation, and evaluation techniques have all been covered.

II. KEY DIFFERENCES

The primary goal of this machine-learning-based analysis system is to assess illness features and generate useful forecasts. Images must be preprocessed, areas of interest associated with the disease must be segmented, compelling features must be computed, and detection and classification models must be built using these features. For instance, the KNN model achieves a 96.4% accuracy in a subset of non-COVID-19 & COVID-19 situations [17]. Somewhere there's a discrepancy with this sum. Several DL models have been published to properly categorize and identify COVID-19 instances. The suggested technique uses deep learning to identify potential covids in chest X-rays. The photos are classified as either infected with COVID-19 or not infected with COVID-19 using this technique. Imaging modalities such as chest X-rays (or radiography) and chest CTs are more useful in identifying lung-related issues.

Nonetheless, a thorough chest x-ray is more cost-effective than a chest CT. Evidence of opacity on COVID-19 X-ray pictures has been found. There were individuals in one research who had ground-glass opacity on both eyes [2]. 50%-60% of children with COVID-19 had consolidation and ground-glass opacities [3]. To aid in the screening of huge quantities of radiograph images for COVID-19 suspicious patients, this essential feature may assist construct a deep learning model.

Among machine learning methods, deep learning has shown to be the most effective, and its analysis of a big dataset of chest x-rays may have a major effect on the effectiveness of the Covid-19 screening program. In this study, we used the PA projection to compare chest x-rays from patients with and without the covid-19 mutation. We will first apply data augmentation and picture cleaning before experimenting with several deep learning-based CNN models and evaluating their results. Deep learning has great promise to greatly improve the efficiency of machine learning for automated lung radiology interpretation. Access to training and testing datasets that allow for repeatability and comparability is crucial in deep learning research. The primary goal of this machine-learning-based analysis system is to assess illness features and generate useful forecasts. Images must be preprocessed, areas of interest associated with the disease must be segmented, compelling features must be computed, and detection and classification models must be built using these features. For instance, the KNN model achieves a 96.4% accuracy in a subset of non-COVID-19 & COVID-19 situations [17].

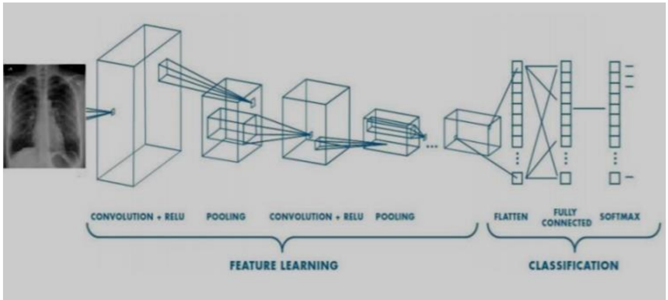


Fig. 1: System overview

The picture collection features both commonplace and unusual things including pencils, animals, buildings, textiles, and geological formations. Methods for transfer learning include keeping the last three layers (classification, completely linked, and SoftMax) frozen. Afterward, the last three layers are taught to identify brand-new data types. Positive outcomes from using pretrained models have been seen, with some cases yielding results on par with seasoned radiologists [11].

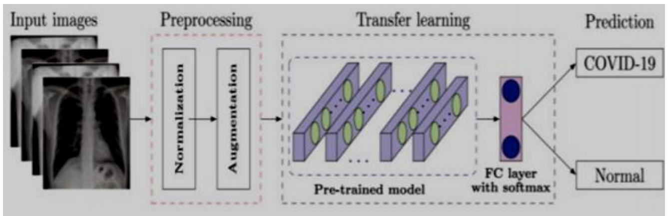


Fig. 2: Transfer Learning

High-quality input data is essential for successful deep learning. Garbage in, and garbage out is a valid maxim for deep learning, including lung radiography deep learning. Research has shown that internal and external variables contribute to radiologists' interpretation mistakes [12].

Some instances of the former are scan, recognition, judgment, and cognitive mistakes, while others include fatigue, overwork, and distraction.

Recently, a dataset [4] of radiologist-judged labels for lung X-ray 14 was developed [11]. These labels are exceptional because they required the review of a panel of doctors who specialize in radiology and have at least three years of experience in general radiology. Using a previously established pre-trained model that was retrained using adjudicated data to recognize images with airspace opacity, a COVID-19 abnormality, this study aims to construct a deep learning model for COVID-19 case prediction in light of the recent discovery of equivocation as a significant feature in COVID-19 patients.

Fig. 3: Step-by-step walkthrough of the solution

III.STEP-BY-STEP WALKTHROUGH OF THE SOLUTION

The steps that are followed are as follows:

- This research obtained chest X-ray pictures of Covid-19 patients, healthy people, and pneumonia patients from the Kaggle repository. We gathered data from 21,025 chest X-rays to build and test our model. Fig. 1. a and 1. b show two examples of chest X-rays taken from different patients. Model building and hyperparameter tuning were done using a 2000 chest X-ray images dataset. In other words, the patient population in the training and test sets were completely separate.
- Image inputs should be resized to fit the size of the input layer of the pre-trained network. Figure 3(a) and 3(b) are examples of Covid x-ray pictures (b).
- You'll need a large amount of data to achieve trustworthy findings from a deep-learning approach. Although, it's safe to assume that there isn't enough information to solve any issue. Particularly when it comes to matters of health, data collection may be a costly and time-consuming endeavor. These problems may be addressed using augmented methods. By augmenting, we can fix the overfitting issue and make the suggested model more precise.
- Modify the network design by exchanging the average pooling, fully-connected layer, and softmax layers of the pre-trained network with a classification output to determine the likelihood of COVID-19 and the regular class.
- Instruct the System.
- Please use the testing dataset to evaluate the classifiers. A collection of chest X-ray images was employed with models InceptionV3, Resnet-50, and VGG-16.
- The model's performance may be analyzed by plotting accuracy and loss with time.
- The task is to create a user interface to identify covid in a radiographic picture.

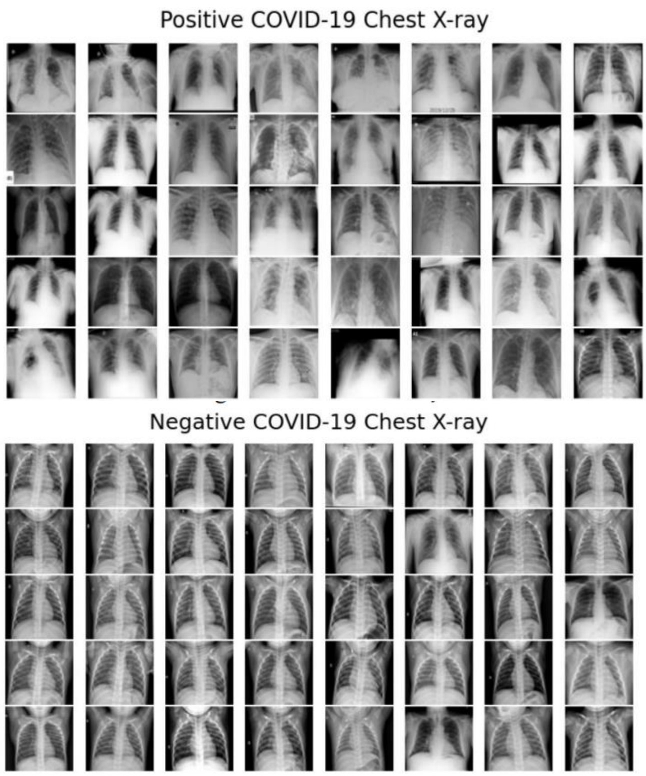


Fig. 4: Covid Positive and Normal Chest Image

IV. MODEL AND MODEL EVALUATION

A. VGG16

Deep Convolutional Networks for Large-Scale Image Recognition, written by Karen Simonyan and Andrew

Zisserman, is credited as the first publication of VGG models. Compared to VGG99's 19 weighted layers, VGG16 only has 16. Because it is so straightforward and reminiscent of the first convolutional networks, the VGG design is widely used. The basic motivation behind VGG was adding more convolutional layers to the network to make it deeper. The small size of the convolutional windows (3x3) allowed for this. This classifier learns from the 1000 labeled images in the ImageNet database. However, we can only utilize two categories since we're only interested in classifying Covid and Normal X-ray pictures. Easily import only the convolutional part of VGG16 by setting the include top parameter to False.

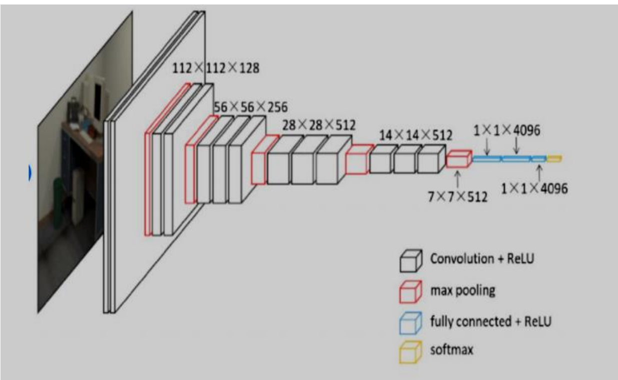
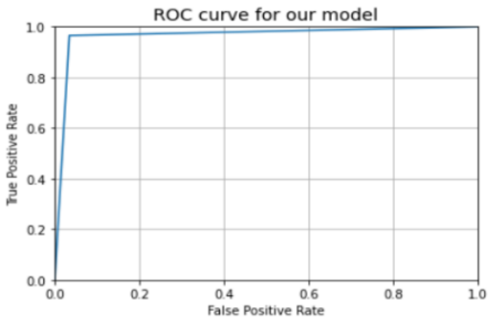


Fig. 5: The classifier



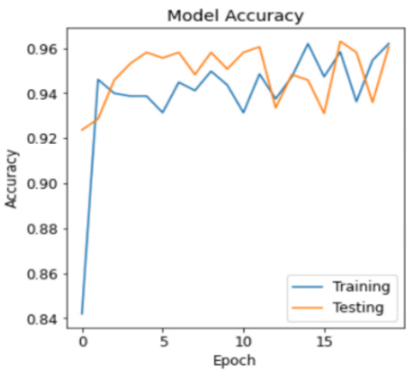


Fig. 6: Epocs and Accuracy

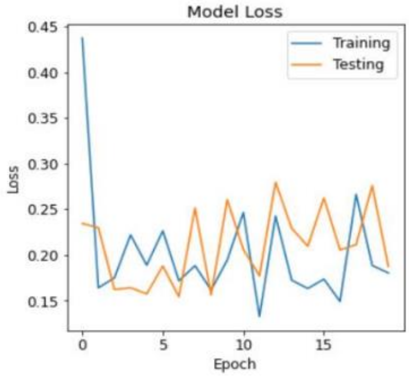
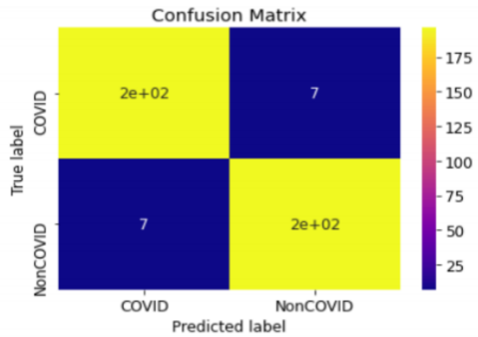


Fig. 7: Loss vs. Epocs (VGG16)

	precision	recall	f1-score	support
0	0.97	0.97	0.97	203
1	0.97	0.97	0.97	203
accuracy			0.97	406
macro avg	0.97	0.97	0.97	406
weighted avg	0.97	0.97	0.97	406

Fig. 8: VGG16 Classification



Confusion Matrix with Normalized Values

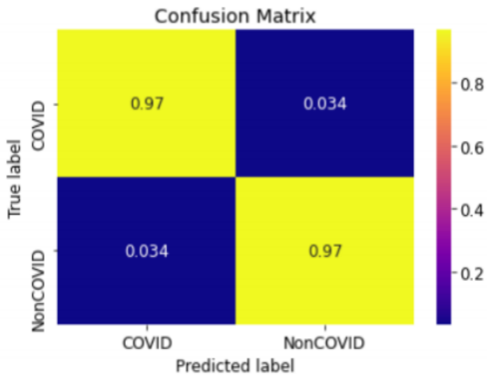


Fig. 9: Confusion Matrix

B. ResNet50

The ResNet-50 network has 50 layers of convolutional neural connections. To access a network that has already been trained on more than a million images, you may utilize the publicly available ImageNet dataset. The network can divide a picture into one thousand categories, such as plants, electronic devices, and animals.

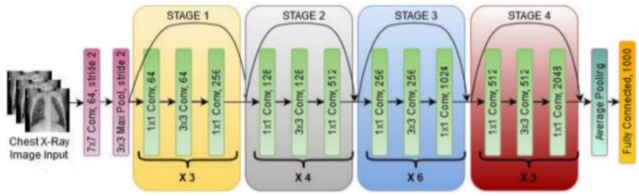
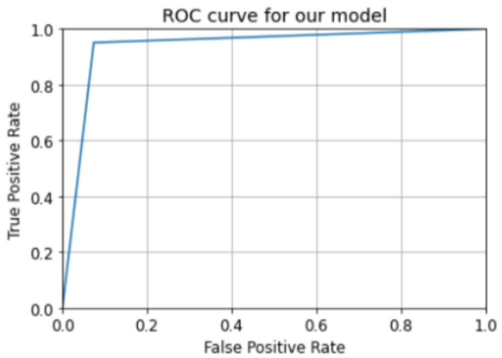


Fig. 10: Architecture of Proposed System

The ROC curve, Classification report, confusion matrix, Model Accuracy, and Model Loss plots are below.



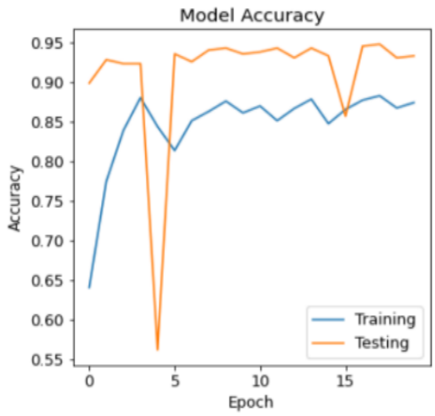


Fig. 11: Epocs ResNet50 and Accuracy

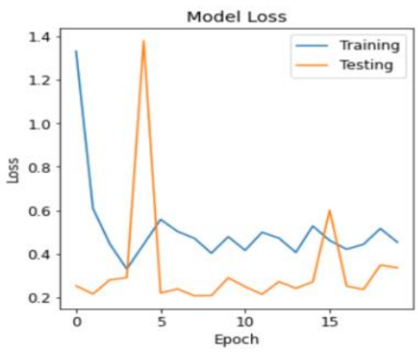


Fig. 12: Loss vs. Epocs (ResNet50)

	precision	recall	f1-score	support
0	0.95	0.93	0.94	203
1	0.93	0.95	0.94	203
accuracy			0.94	406
macro avg	0.94	0.94	0.94	406
weighted avg	0.94	0.94	0.94	406

Fig. 13: Classification Report for ResNet50

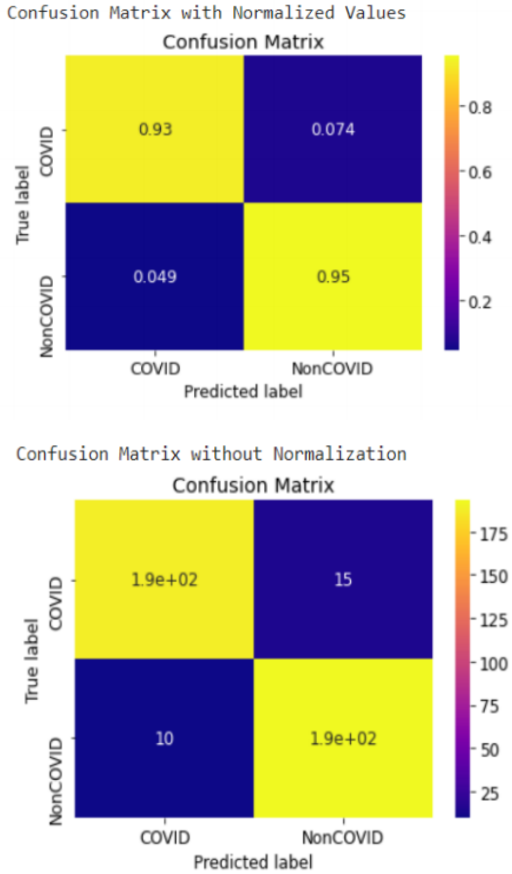


Fig. 14: Matrix

C. Inception V3

Specifically, Inception-V3 is a 48-layer deep convolutional neural network. Using the ImageNet database, you may access a network version that has already been trained on more than a million images. Photos taken with this network may be sorted into one thousand distinct categories, such as keyboard, mouse, pencil, and animal. Therefore, the network has acquired rich feature representations for many different classes of images.

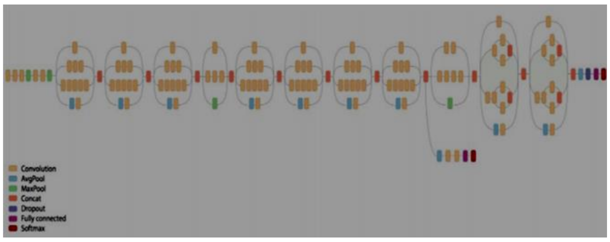


Fig. 15: Architecture

V. COMPARISON TO BENCHMARK :

Table 1: Comparison of benchmark

Model	No. of parameters	Testing Accuracy
VGG-16	20,074,562	97
ResNet50	23,788,418	94
Inception V3	23,788,418	94

As we can observe from our models' accuracies, The maximum accuracy was attained with VGG-16, followed by RestNet50 and inceptionV3.

VI. VISUALIZATION

As of late, transfer learning has been a popular deep learning technique used in a computer vision system (TL). Rather than beginning the learning process from zero, TL allows us to develop an accurate model using patterns acquired from solving diverse problems [56, 57]. Therefore, it is time-efficient and produces high-quality results even with a limited data set. There are two stages to the process of transfer learning. The initial phase of transfer learning is picking a DL model that has already been trained. We may choose from a plethora of already trained models in the literature, all of which have been trained on massive benchmark datasets and are therefore well-suited to tackle the challenge we set out to address. Keras, for instance, has a large library of pre-trained models including VGG, Inception, and ResNet. Then all that remains is to choose the one that will do the job best. The model then has to be tuned depending on the amount of our dataset and how well it matches the pre-trained model's dataset. For example, if we have a huge dataset distinct from the dataset used to train the model, we will need to retrain the whole model.

It is a common problem in ML models that they overfit. When a model memorizes the training dataset without absorbing its essential properties, trends, and limits, this phenomenon manifests itself. Then its effectiveness on new information is compromised. On the other hand, overfitting is suspected when the model's accuracy is high for the training data but declines dramatically when presented with fresh data. Overfitting occurs in training when no data augmentation is used, as seen in Figure 3. To lessen the impact of the overfitting issue, many methods exist. Increasing the available training datasets is the first step toward a solution. Second, enriching the data with operations like picture rotation, magnification, and flipping the image horizontally or vertically is helpful.

Finally, dropout regularisation, L1 regularisation, and L2 regularisation are all viable choices. The overfitting issue may be mitigated, at last, by adopting a model with fewer layers and neurons. Normal feature extraction occurs at the convolutional layer. The flattened layer follows the convolutional base and converts the feature matrix from two dimensions to a vector. Then, we passed the result into a softmax activation layer for final classification. All of these networks use an optimizer called 'rmsprop,' an input size of (224, 224, 3), an initial learning rate of 0.001, a batch size of 32, and a total of 50 epochs. Since the result has plateaued, we have implemented the Keras callback function ReduceLROnPlateau to slow down the learning rate. The learning rate will slowly slow by a factor of 0.3. The network's overfitting issue is mitigated in part by this function. Examples of feature maps produced from the VGG network's first convolution layer are shown in Fig. 1-(c). It's proof that the TL method may be used to glean useful data from photos.

A. VGG16

In 2014, the ILSVR(Imagenet) competition was won by the VGG16 CNN architecture. It's one of the best vision model architectures out there right now. Two fully connected (FC) layers precede a softmax output layer at the end. The number 16 in VGG16 indicates the number of weighted layers it contains. This network contains a huge number of parameters—around 138 million.

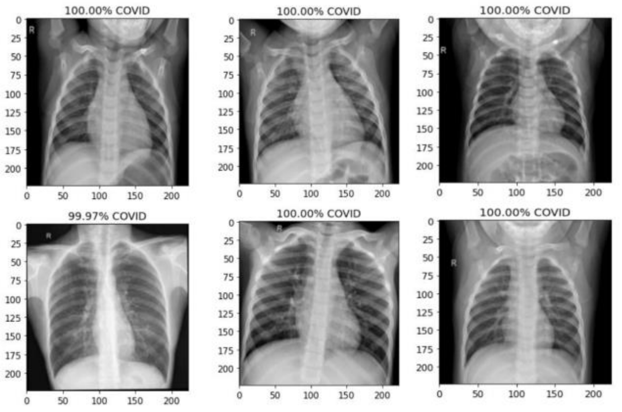


Fig. 16: Visualization by VGG16

B. ResNet50

ResNet50 has been the most interesting breakthrough in computer vision and deep learning. ResNets' design makes it possible to train extraordinarily deep neural networks with hundreds or thousands of layers while maintaining great performance. Image recognition was the original application of ResNets, but the paper suggests that the framework may be used for other, non-computer vision issues with the same results. Given that adding more layers also increases accuracy, some may wonder why we required Residual learning to train incredibly deep neural networks. It is well-known that Deep Convolutional neural networks perform very well when tasked with extracting low-, medium-, and high-level properties from images.

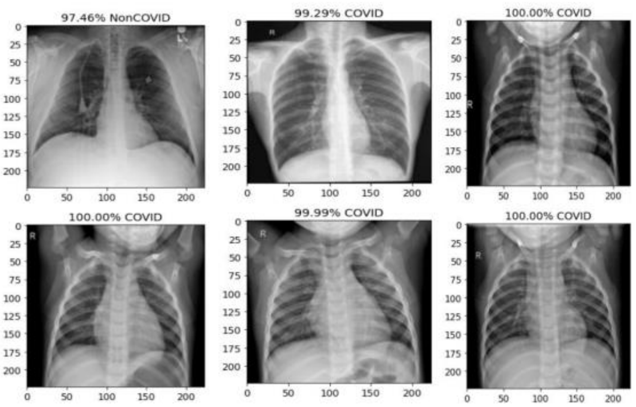


Fig. 17: Visualization by ResNet50

C. INCEPTIONV3

Similarly to how ImageNet is a library of labeled images, Inception is a tool for classifying images in the field of computer vision. As a result of its success, the Inceptionv3 architecture has been adopted for usage in a wide variety of other projects, often pre-trained using data from ImageNet. In the field of biological sciences, for instance, it has been put to use in studies about the study of leukemia. After an online meme repeating a line from Christopher Nolan's Inception went viral, the original name was changed to this codename.

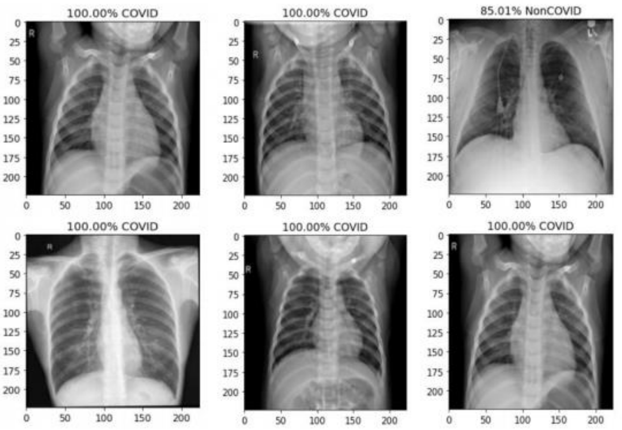


Fig. 17: Visualization by InceptionV3

VII. GUI

The VGG models' accuracy was superior to those of the RestNet and Inception models. The radiographic picture is read by a Flask-based UI, which feeds the data into a VGG Model for prediction. Based on the chosen picture, the prediction result will be a binary classification of covid/normal detection. It has Flask APIs that take in information about radiographic images through a graphical user interface (GUI) or API calls and then uses vgg to predict a value and return it. Its client-side HTML/CSS style lets consumers inspect pictorial info while away from their computer. It uses the POST method on the REST API(/detect) to deliver the picture data and then reports whether or not the covid detection was positive.

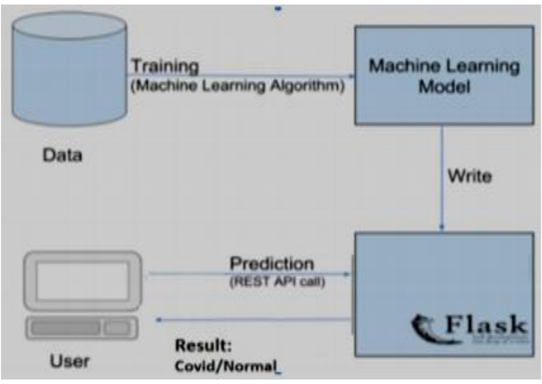


Fig. 18: Pipeline for Development of Model including UI

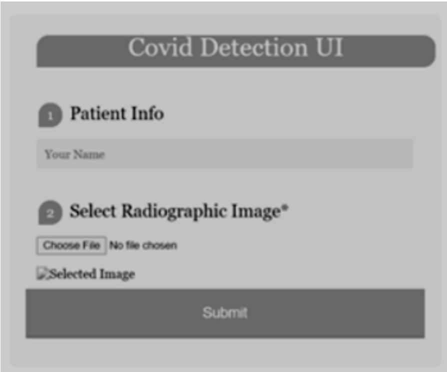
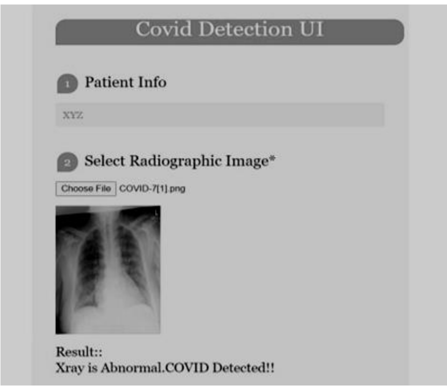


Fig. 19: Select Image from Covid Test Images



Select a normal image. Result is detected as normal.

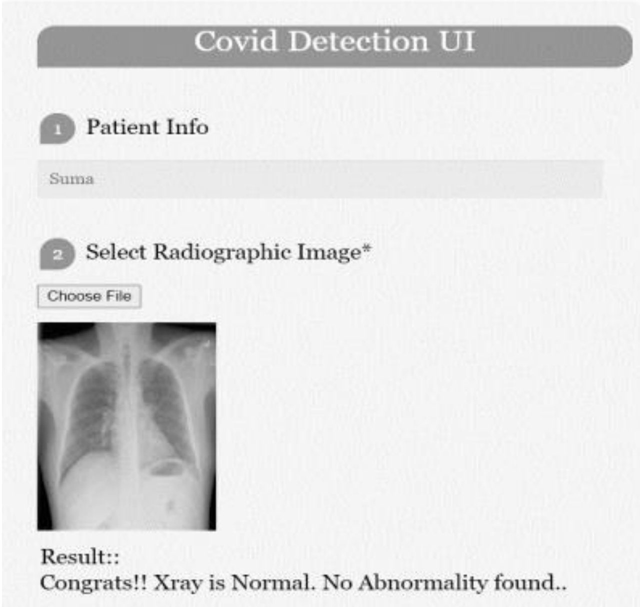


Fig. 20: Detected Result

VIII. API Sample Usage

A. Covid Image

Fig. 21: Detected Covid in Result

B. *Normal Image*

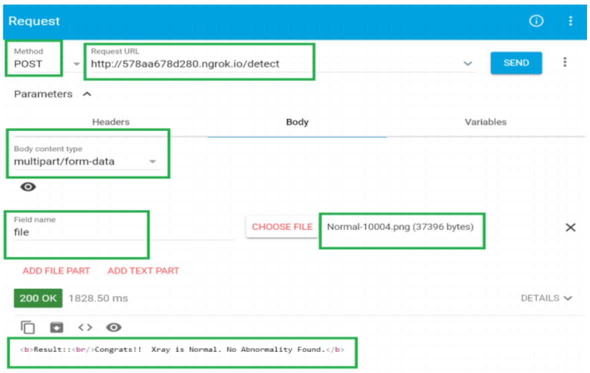


Fig. 22: Detected Normal Image in Result

C. *Implications*

This research presented a deep learning-based system to identify and categorize COVID-19 cases in X-ray pictures. With our model's comprehensive framework, feature extraction is unnecessary. Our approach has the potential to achieve a performance accuracy of 97%. This method may help alleviate the lack of radiologists in remote parts of COVID-19-affected nations. In the future, we want to verify our model by including more photos. This model may be saved in the cloud after it has been created to facilitate speedy diagnosis and assist in the rehabilitation of afflicted individuals. The clinical workload should be much reduced as a result of this.

Deep learning techniques need large input data before producing trustworthy outcomes. However, there is probably not enough information to solve any issue. Particularly when it comes to matters of health, data collection may be a costly and time-consuming endeavor. We hope that by utilizing more similar photographs in the future, we can strengthen our model and improve its accuracy.

IX. CONCLUSIONS AND FUTURE WORK

The COVID-19 coronavirus infection is threatening the life of billions of people because of its extremely contagious nature. According to WHO, infected people and deaths are increasing rapidly. This viral infection inflames the lungs of the infected people. Therefore, one of the possible approaches to recognize those inflames by chest x-ray. In this study, we have presented an automated CAD technique to detect COVID-19 cases from pneumonia and healthy cases using chest x-ray images. We have utilized 15 deep transfer learning models, and the performance is evaluated using different metrics. The results confirm that the VGG series are the most suitable models for this task. Though CNN achieves maximum results in medical image analysis tasks, there is still scope for development. First, researchers can develop a partly new CNN model to analyze COVID-19 chest X-ray images by selecting the top CNN models, finding their respective advantages, and merging their best parts to enhance the final classification performance. Secondly, there is a scarcity of publicly accessible COVID-19 CXR image datasets. Therefore to develop a publicly accessible database would be beneficial for future researchers. In the prospect, we intend to develop a more efficient CNN structure to identify COVID-19 cases from CXR images. Thirdly, selecting the top CNN models and combining them with classical image features will be easier to link machine-learned knowledge and human knowledge together to obtain an even better classification performance. Fourthly, though the texture feature is a low-level feature, it is useful for adequately explaining the image content (such as in the field of fracture detection techniques in bone X-ray images [63]). Therefore, a combination of some texture descriptors such as content descriptor [64] (local binary patterns, edge detection histogram) and local density features [65] with deep learning features can lead to a superior performance of the model. Fifthly, Noise is one key factor in digital radiography responsible for degrading the model performance. Consequently, in the preprocessing step, generative adversarial network (GAN) [66, 67], non-local mean filter [68], fuzzy genetic filter [69], and robust navigation filter [70] based x-ray image denoising method can bring a significant improvement of the model performance. Finally, an application of the feature fusion (or ensemble learning) technique to the best-performing CNN models can enhance the final classification performance [71]. Here, it will be easier for the practical development of software.

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