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# COVID-19 Detection Using Convolutional Neural Networks and InceptionV3

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***Abstract*— The world today faces the grave crisis of a pandemic that threatens life, health, industries, economies and society as we know it. To tackle the spread of the COVID-19 disease, it is imperative that the individuals affected by it are identified efficiently. The medical workforce is overwhelmed in many countries, and doctors and nurses must be assisted with rapid automated systems that detect COVID-19 confidently without the need for trained personnel or special manufacturing processes. The currently available testing mechanisms are accurate but take up to 5 days to show results. Automated radiological testing is faster and does not require any testing kits. This study aims to simplify, speed up and validate the process of COVID-19 detection and differentiation from other lung diseases using Artificial Intelligence and Machine Learning principles to implement a cost effective and accurate COVID-19 test by detection of inflamed parts of lungs in chest X-Rays. Two approaches for separate target users are built. In the first approach, a customized Convolutional Neural Network model is built to classify chest X-ray images into two classes- 0(COVID-19 negative) and 1 (COVID-19 positive). This model reached an accuracy of 98%. The Inception v3 architecture (GoogLeNet) was trained for the second application, in which people infected by COVID-19 were distinguished from patients of other underlying lung diseases such as Atelectasis and Pneumonia. This approach demonstrates how reliably an automated COVID-19 test can be extended to people with other lung complications and showed a 91% accuracy.**

***Keywords*— *COVID-19, Convolutional Neural Network, Inception v3, Computer Vision , Deep Learning, COVID-19 testing, Radiology***

## I. INTRODUCTION

In the years 2020 and 2021, over 3.2 million deaths have been recorded due to the spread of the novel Corona virus. Lives of billions around the globe have been severely affected by these unprecedented circumstances. The close of industries, loss of jobs and overwhelmed healthcare systems have led to financial crises in multiple nations and had an effect on the pandemic on 5 economic sectors [1]. Curbing the rapid spread of the virus is the need of the hour and a crucial step towards this is identifying individuals infected by COVID-19.

As of today there are predominantly 3 COVID-19 detection tests being manufactured, each with setbacks and strengths of their own.

PCR: While the PCR test is considered to be the most reliable, it is not feasible for usage in remote and rural areas owing to the laborious processes of manufacturing, deployment and distribution. Moreover it requires 24 to 48 lab hours to run and derive PCR test results. According to a study on PCR accuracy, when the test is used in areas where the disease isn't very prevalent, it diagnoses precisely in only 55% of the cases [2].

Antigen Test: It is a cheap and speedy test, but lacks accuracy and is susceptible to giving a sensitivity of 29.5 to 79.8 , which leads to increased false negatives [3]. False negatives are to be treated critically as they put people under the false impression that they are free of infection, leading to a more rapid spread.

Antibody Test: This test is the most unreliable of the three, owing to the unpredictability of antibody production in different patients. Substantial antibodies are found to be produced only a week after infection leading to low sensitivity of the test. Though helpful for population level surveys, it does not give much insight for individual cases [4].

One of the major shortcomings of current testing mechanisms is the lack of trained manpower required to conduct molecular biology experiments, (e.g. viral RNA extraction and qPCR), specially in developing countries that do not have a competent healthcare system [5]. Radiology images have been successfully used in deep learning algorithms to detect Pneumonia in patients who have effects on lungs similar to the ones observed in COVID-19 infected patients [6]. X-rays and CT Scans provide a reliable alternative to antigen and PCR tests that does not require any special manufacturing process. It is understood that though it may not yet be feasible to replace current COVID-19 detection tests with AI systems owing to insubstantial data availability, it is most certainly an area worth exploring. In a comprehensive paper of the upcoming role of AI in the battle against the pandemic, Nguyen writes "We observed that there are still relatively limited applications and contributions of AI in this battle. This is partly due to the limited availability of data about COVID-19 whilst AI methods normally require large amounts of data for computational models to learn and acquire knowledge. However, we expect that the number of AI studies related to COVID-19 will increase significantly in the months to come when more COVID-19 data such as medical images and biological sequences are available." [7, p.7]

There are still many aspects in COVID-19 testing that need research and rectification and AI techniques on radiology images show promising results.

## II. METHODOLOGY

In this paper, Image Processing and Machine Learning models were employed to take two different approaches to make an automated COVID-19 detection system using X-rays. Hence, two separate datasets were used.

In approach 1, the objective is to test healthy individuals (with no other lung conditions) for a COVID-19 infection. In this approach, a CNN model with customized architecture is trained to give output between 0(COVID-19 -ve) and 1(COVID-19 +ve), denoting how confidently it lies in that class.

In approach 2, the objective is to determine whether a neural network can distinguish between a COVID-19 infection and other lung abnormalities, and whether this testing mechanism could be extended to people with other complications in their lungs (Pneumonia, Atelectasis, Rib fractures, Edema, Lung lesion, etc). The radiology images of patients with COVID-19 have similarities with patients having other lung diseases [8]. This approach uses a powerful state of the art model architecture by Google named Inception v3 (GoogLeNet) to build a classification system that distinguishes between various other lung complications and COVID-19 infections. The performance of this model determines if an automated COVID-19 detection system could be safely used on patients with other underlying lung conditions.

## III. DATASETS

For the two different approaches taken, two datasets were used. The URL for the images used is provided here.

- Dataset 1: This Dataset contains chest X-Ray images of healthy lungs with no abnormalities and those of COVID-19 patients.
- Dataset 2: This Dataset consists of chest X-Ray images of patients of Pneumonia, Atelectasis, Rib fractures and other lung conditions along with COVID-19 infected patients.

The images in the datasets used for model have been verified by a certified radiologist. The images initially existed in varying sizes and resolutions and were later resized to homogeneous size of 200 X 200. In the second approach, due to lack of data availability of images from patients with lung disorders, augmentation techniques (flip, rotate, etc) are performed.

The principle of X-Ray imaging is that different materials in the body absorb different amounts of radiation. Each type of tissue will hence be represented by a different shade of grey. The image pixel values range between 0 and 1 depending on how bright or dark they are. In a study concerning the visual changes in lungs as the virus enters through the respiratory tract of the patient, it was observed that hazy spots (called ground glass opacities in medical terms) due to inflammation developed in certain areas of the lungs [9].

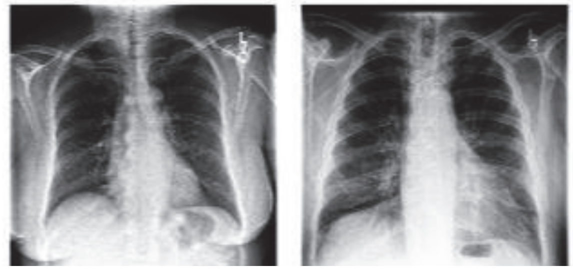

Fig. 1. Two samples of healthy lung X-Rays from

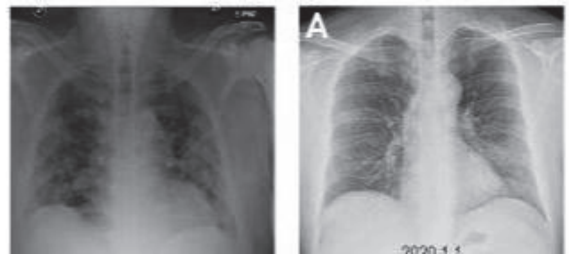


Fig. 2. Two samples of COVID-19 infected lung

On closer inspection, one may be able to discern the dissimilarities between the former set of images and the latter.

Though the ground glass opacities are not dense enough to hide out the bronchioles, they are easily captured in X-Ray images and CT scans, making both these imaging techniques suitable for the application at hand.

## IV. MODELS

### A. *Approach 1 (Customized CNN)*

In the first approach, a customized Convolution Neural Network model is trained on images from a dataset in which only X-Rays of healthy lungs and COVID-19 infected lungs were present. The output of this network gives a probability which lies between 0(COVID-19 -ve) and 1 (COVID-19 +ve), denoting how confidently it lies in that class.

The Convolution neural networks are regularized versions of multilayer perceptron (MLP). CNN are neural networks over which we use a technique called convolutions. Consider an image which has size 100 x 100 x 3. The array which will represent this image will also have the size 100 x 100 x 3 and the values inside the matrix will vary from 0 to 255. These values describe the pixel intensity at that part of the image, where 0 represents black and 255 represents white. In a CNN, we use something called a filter, which is also a small matrix which we multiply over the image array. This filter is usually of the size 3 x 3 or 5 x 5, though the filter sizes can go up to 11 x 11 too. The filter is filled with random values. The filter is used to extract certain features of the images. Each filter is considered a feature identifier, so when a certain feature of the image matches the filter, it gives a relatively higher value after multiplication. Thus, a larger value corresponds to the feature being present and vice versa. Since images have a large number of pixels or features, CNNs are specifically efficient in classifying images as they substantially reduce the number of features without compromising on the model quality. For these reasons, a CNN was chosen for classification in the first approach.

A 2-D Convolution Neural Network uses the Keras API to build the CNN, which uses Tensorflow as its backend. In the first layer, a 32 neuron convolution and a convolution kernel size of (3 x 3) is used. A (3 X 3) kernel is the standard size as it corresponds to a good compromise between computational complexity and quality of the resulting image.

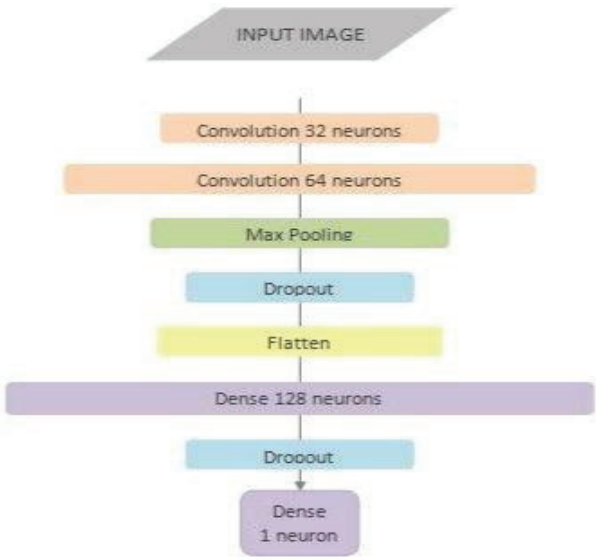


Fig. 3.The architecture of the Customized CNN

With the exception of the last layer, all the network layers use the activation function "ReLU". This function is a simple yet powerful activation that allows the neuron to train only if the input is relevant. In mathematical terms, the output is positive only if the input is positive, otherwise it is 0. The second convolution layer consists of 64 neurons with the same filter size and activation function. This is followed by a Pooling layer that selects the maximum pixel value from sub matrices of (2 X 2) size, hence reducing the Image quality. The succeeding Dropout layer is a Regularization technique that reduces over-fitting (excessive specific learning) on the training data. It drops out random neurons during training at a 0.5 dropout rate.

A 128 neuron dense layer with activation function ReLU and dropout 0.5 is added and lastly, the model ends with a single neuron that determines the final output of a particular input. This neuron uses the sigmoid activation function, which invariably gives an output between 0 and 1.

This architecture provides a simple, firm and time efficient classification model.

### B. *Approach 2 ( Inception v3 using Transfer Learning)*

This approach uses a powerful state-of-the-art model architecture by Google named Inception v3 (GoogLeNet). It is trained on a dataset that contains patients of other lung diseases such as to build a classification system that distinguishes between various lung complications and COVID-19 infections. The performance of this model determines if an automated COVID-19 detection system could be safely used on patients with other underlying lung conditions.

This model architecture is based on a modification in the Inception architecture specifically for Computer Vision application [10]. An inception module is, simply put, a specific combination of (1 X 1), (2 X 2) and (5 X 5) convolutions which are supplemented by Max Pooling layers. The above mentioned inception modules are stacked to create a 48 layer model architecture.

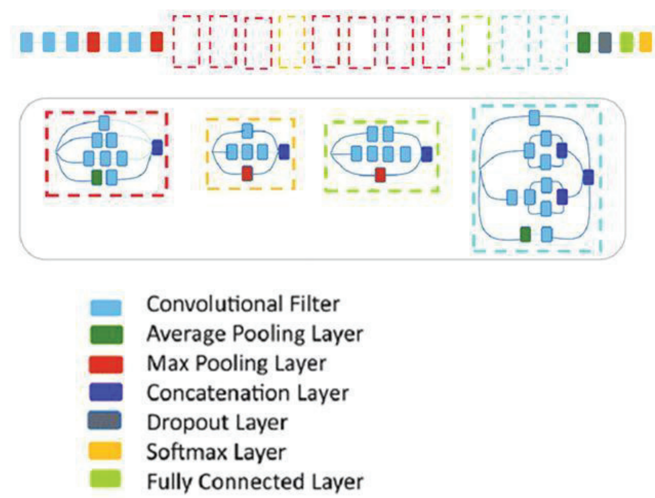


Fig. 4. An illustration of the GoogLeNet Architecture

Traditional models with densely connected layers are prone to over-fitting. Moreover, the increased number of trainable parameters implies more requirement of computational power. Inception v3 architecture resolves these setbacks by employing sparsely connected rather than densely connected layers. Using smaller and asymmetric convolutions is another way the Inception v3 module succeeds in deducting the computational power usage. This architecture gives a combination of efficiency along with parameter reduction, and is a cutting edge model used for Image Classification, and hence was chosen for the more challenging classification in approach 2.

### C. *Transfer Learning*

A game changing methodology called transfer learning can be included in the Inception v3 model training process. 'Transfer Learning', as the name suggests, transfers what the model learns from an extensive data source to any application that requires them. In this case, the Inception v3 model architecture has been pre-trained on over a million images from the ImageNet dataset, and these weights are reused while training the model on the current dataset. This generally gives this model architecture an edge over regular models. However, it must be noted that if the pre-training takes place on grayscale images instead of the RGB images of ImageNet, both the speed and accuracy for medical image processing will increase [11]. Hence, assuming an availability of training datasets specific to medical imaging, training on single channel images will prove to be beneficial.

## V. TRAINING

Due to the different datasets and target users of both the models, a drastic difference between their training processes was observed.

### *A. Approach 1 (Customized CNN) Training*

With a learning rate of 0.001 and the Adam optimizer, this model trained over 15 epochs.

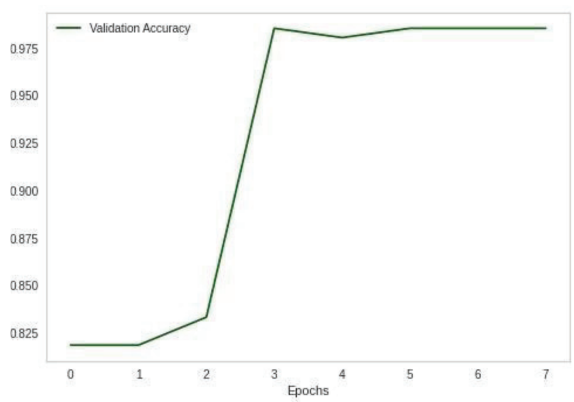


Fig. 5. Accuracy variation of Customized CNN

As seen, the accuracy increases drastically till the 3rd epoch, reaches 98% and then remains constant (Early stopping ends the training process).

### *B. Approach 2 ( Inception v3) Training*

This model performs the more challenging task of classifying between other lung abnormalities and COVID-19 infection in lungs. Many lung diseases included in this comparison have effects on lungs visually similar to those of a COVID-19 infection. The differences between the two are not as obvious, and require more computation and deeper comprehension to be classified. Consequently, this model shows an inconsistent trend while training. This model uses a learning rate of 0.0009 and Adam optimizer and 50 training epochs. The validation accuracy shows extreme fluctuations, which indicates that the model often confuses other lung abnormalities with a COVID- 19 infection.

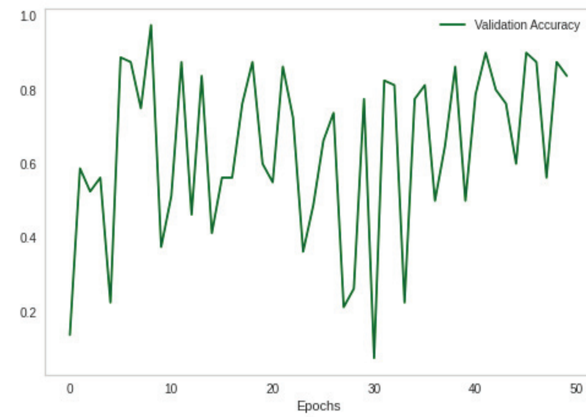


Fig. 6. Accuracy variation of Inception v3

## VI. EVALUATION

Based on their applications and largely varying datasets, evaluating both the models gives an insight into their reliability in their respective domains. The Performance metrics relevant to the application are Accuracy, f1 score, Sensitivity and Specificity.

- Accuracy: A measure of correctly predicted cases. It treats both classes with equal importance.

Accuracy = (True Positives+True Negatives)/Total (1)

- F1 score: It penalizes incorrect predictions and hence is suitable for applications where False Positives and False Negatives are to be assessed critically.

F1 Score = 2(Precision*Recall)/(Precision + Recall) (2)

- Sensitivity: It measures the percentage of correctly predicted positives out of all the infected patients.

Sensitivity = True Positives/(True Positives + False Negatives) (3)

- Specificity: It measures the ability of a test to correctly flag negative results.

Specificity = True Negatives/(True Negatives + False Positives) (4)

TABLE I. PERFORMANCE METRICS OF CNN AND INCEPTION V3

| | **Approach 1 (CNN)** | **Approach2 ( Inception v3)** |
|---|---|---|
| Accuracy | 0.98 | 0.91 |
| F1 score | 0.974 | 0.913 |
| Sensitivity | 0.91 | 0.86 |
| Specificity | 1.0 | 0.963 |

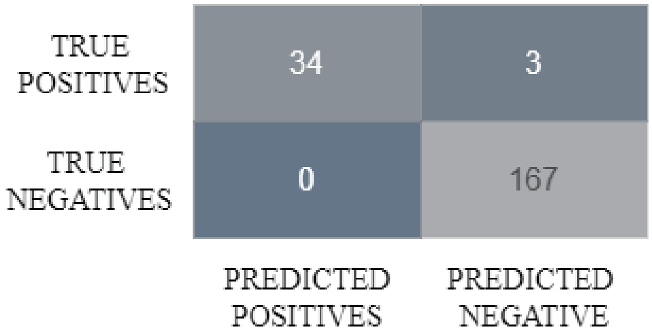


Fig. 7. Confusion Matrix of Customized CNN

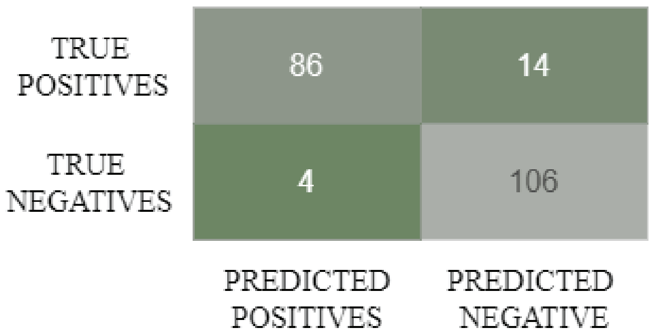


Fig. 8. Confusion Matrix of Inception v3

It is evident that the CNN model performance is superior to the Inception v3. This can be attributed to the ideal dataset that it trained on. The Inception v3 model on the other hand shows satisfactory but not exemplary performance.

## VII. CONCLUSION

As is evident from the performance metrics of the customized CNN model, healthy patients with no underlying lung diseases may easily switch to automated classification using X-ray imaging and expect 98% accurate results. The results of Approach 2 show that patients of Pulmonary Edema, Pneumonia, Atelectasis, etc must only use automated radiology testing as faster supplements to existing testing mechanisms and professional medical advice. It is to be noted that a model with increased competency for this application may be obtained by applying Transfer Learning on its weights with a more specific 1-channel X-Ray dataset as opposed to the general 3-channel ImageNet dataset.

Densely populated countries with inadequate healthcare facilities are subject to economic downfalls and subsequently, social unrest. The emergence of a functional vaccine does not guarantee that remote areas and financially disadvantaged divisions of society have immediate access to it. The vaccination system could bring betterment to some parts of the world, but without consistent effort to curb the virus, may lead to further degeneration of others. The unparalleled courage of our frontline workers must be assisted with innovative use of available technology to impede the spread of COVID-19 until the people of the world recover physically, financially and emotionally.

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