Covid-19 Detection Using Multi Modal Imaging Data

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ABSTRACT

The COVID-19 pandemic has spread rapidly across the globe and has caused life threating consequences to mankind ever since it started from Wuhan, China in December 2019. Early Detection and Prevention can help in containing the spread of the disease. Screening of large number of people is pressing priority. One of the crucial steps towards achieving this goal is through radiological examination. The approach we followed aims to remove unwanted noise from images so that the deep learning models can focus on detection of disease. The results prove that Ultrasound imaging is far more superior than X-Ray and CT scan. In this study, we identify a suitable Convolutional Neural Network (CNN) model that will detect the Covid-19 Positive patients using chest X-Ray images. Images of Covid positive and negative patients are divided into trainable images and testing images. This test can be done on any computer and by any medical examiner or technician to detect COVID-19 in a matter of few seconds.

Keywords: - *COVID-19 Detection, Deep Learning, Convolutional Neural Network, Radiological Imaging, CT scan, Ultrasound.*

I. INTRODUCTION

The novel CORONA VIRUS disease (COVID-19) is a deadly disease and looking at the extent of its spread all through the world, it has been declared as a global emergency. The pandemic caused immense stress and rate of spread of CORONA VIRUS (COVID-19) was shocking. Governments of various nations are forcing border limitations, flight limitations and social distancing and expanding the awareness of cleanliness. However, the virus is still spreading at a very startling rate. Early detection, isolation and care for patients is the fundamental strategy for handling the current situation. Our study aims to provide a conceptual transfer learning framework to aid COVID-19 detection with using deep learning through CNN models for multiple imaging modes including X-Ray, Ultrasound, and CT scan.

The bulk of the people affected by COVID-19 experienced infection directly on the respiratory tract. Although people of all age groups are at risk of getting the disease, older people face considerable risk of developing illness if they contract the disease due to physical changes that come with age. There are assumptions that elderly people with basic clinical issues like cardiovascular ailments, diabetes, respiratory tract infection, renal or hepatitis and malignant growth are sure to create genuine disease. Total cases are 84,644,904 and 1,837,138 deaths in about 191 countries/territories and 26 cruise/naval ships as on 3 January 2021.

Until now, there is no particular vaccine or treatment for COVID-19. It has been revealed that the spread of the sickness is compelling screening of patients and clinical care. The highest-level screening strategy used for testing the COVID-19 patients is the Reverse Transcription Polymerase Chain Response (RT-PCR) test. This application is that the most widely used technique for testing of COVID-19 however could also be a laboring unsettling, unyielding, and time-consuming process, results taking up to two days.

In this test small quantity of viral RNA are taken from a nasal swab, amplified, and assessed with virus. The detection is indicated visually using a fluorescent dye. Some studies have also shown false positive in PCR testing. Promptly radiological imaging is another major instrument for COVID-19 detection. Most of the CORONAVIRUS cases have comparable highlights on radiographic photographs including multi-focal, ground-glass opacities with fringe dissemination.

There are various testing imaging technology- based approaches which include computed tomography (CT) imaging, X-Ray imaging, and Ultrasound imaging. The CT scan-based detection is time consuming, tedious and manual with the requirement of expert participation. CT scan machines are hard to be utilized for COVID patients, as the patients are required to be taken to the CT room, the machines would need extensive cleaning after each use, and higher radiation risks. Although CT is not recommended as a primary diagnostic tool, it has been successfully used as a supporting tool for COVID-19 condition evaluation

Both the PCR tests and CT scans are expensive and with an immense demand many countries are forced to do selective testing for only high- risk population. X-Ray imaging is comparatively cost effective and commonly used for lung infection detection and can be used for COVID-19 detection as well.

The characteristics observed in the X-Ray images of patients with COVID-19 are patchy infiltrates or opacities. X-Ray images do not show any irregularities in the early stages of COVID-19. However, as the disease advances, COVID-19 gradually manifests as a typical one-sided patchy infiltration involving mid zone and upper or lower zone of the lungs, occasionally with evidence of a consolidation.

Ultrasound imaging has also been recommended as a tool for COVID-19 lung condition evaluation since it can be used at bedside with least infection spreading risks and has exceptional potential to detect COVID-19.

II. RELATED WORKS

Screening of large magnitude of people is of utmost importance so as to curb the spread of a disease within the community. Though, real-time PCR may be the standard diagnostic tool used for pathological testing, the increasing number of false test results has opened the trail for exploration of other testing tools. Chest X-Rays of COVID-19 patients have proved to be a vital alternative indicator in COVID-19 screening. But again, accuracy is largely dependent upon radiological expertise. A symptomatic advice system can aid the doctor to look at the lung images of the patients. Thus, reducing the diagnostic implications of the doctor. Deep Learning techniques, especially Convolutional Neural Networks (CNN) [3], have been successful in medical imaging classification. Four types of different deep CNN architectures were investigated on chest radiograph images for diagnosis of COVID-19. These models are pre-trained on the ImageNet database thereby reducing the necessity for big training sets. It was observed that CNN based architectures have the potential for diagnosis of COVID-19 disease [3].

The focus is to supply the excessively pressurized medical professionals “a second pair of eyes” through intelligent deep learning image classification models. A suitable Convolutional Neural Network (CNN) model was selected through beginning comparative study of several popular CNN models. The selected VGG19 model was then improved to meet the needs for the image modalities in regard to the highly scarce and challenging COVID-19 datasets. We accentuate the problems (including dataset size and quality) in using current publicly available COVID-19 datasets for improving useful deep learning models. We also provide a picture pre-processing step to provide a reliable image dataset for improvising and examining the deep learning models. The new approach is aimed to chop back unwanted noise from the images so as that deep learning models can focus on detecting diseases with specific features from them.

X- ray machines use radio waves as radiation to look at the affected parts of the body in case of cancers, lung diseases, bone dislocations, and injuries [2]. Meanwhile, CT scans are used as sophisticated X-ray machines to examine the soft structures of body parts for better view of specific soft tissues and organs. The main advantage of using X-rays over CT scans are that X-rays are quicker, safer, simpler, and less harmful than CT scans. Narin et al [1] proposed a Convolutional Neural Network-based model to identify covid infected patients using 341 X-ray images of covid patients, 2800 healthy (normal) X-ray images.

He applied this concept in 3 Convolutional Neural Network models: Residual Network-50, Residual inception v-3, and inception Convolutional Neural Network using five-fold cross-validation and submitted the report that Residual Network-50 had the detection accuracy (98%) [2].

Another similar study conducted by Sethy and Behera where the authors extracted the attributes using Deep Convolutional Neural Network algorithm from chest X-ray images and classified images as either infected or healthy using a SVM [3]. They collected two datasets the first dataset contains the collection of 25 infected patients' images and 25 non-infected patients' images while the other dataset contains X-ray images of 133 infected patients and 133 non-infected patients. They applied separate feature extractions on each dataset using various models and achieved a 94.38% accuracy with ResNet- 50 and SVM [3].

III. METHODOLOGY

Data Collection:

In our proposed method, we require sets of images of X-Ray, Ultrasound and CT scan of COVID-19 infected and non-infected patients. The obtained images are characterized based on the uniformity, brightness, contrast and visible difference in size. All the images are collected from GitHub or Kaggle database. But the X-Ray, Ultrasound and CT scan images of COVID-19 infected patients have been largely inconsistent in their parameters of exposure and behavior. The collected datasets are used to differentiate a covid infected patient from a normal patient.

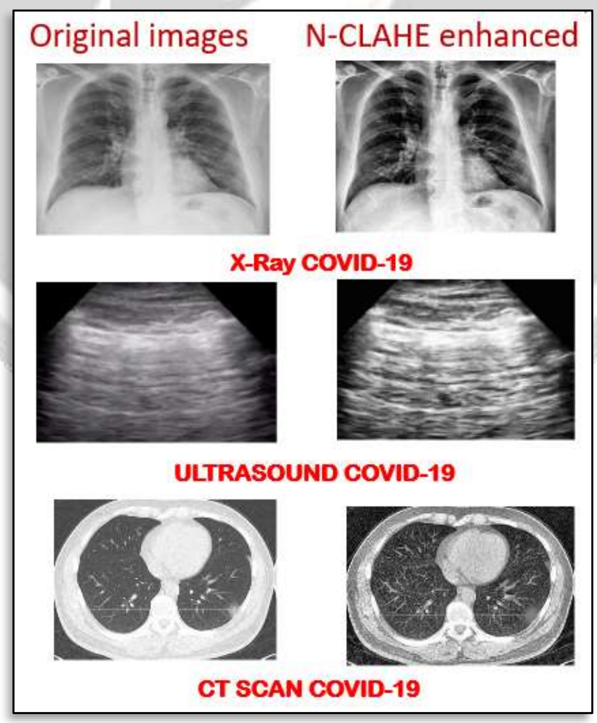


Fig -1: Comparison of Original and enhanced images

Classification Pipeline:

The unprocessed X-Ray or CT scan or Ultrasound image is taken as input and is passed through three layers – Pre-processing layer, pre-trained model and through the additional layer. In the Pre-processing layer, N-CLAHE is applied to normalize the images and to enhance the finer details, textures and contrast of the affected area, so as to facilitate better detection and improve efficiency. After the Pre-processing, the image is augmented.

Augmentation is applied to increase the dataset and improve the performance of the model. It involves horizontal flip, width shift, rotation or height shift.

Then, the augmented image is sent to the pre-trained model which is composed of multiple CNN layer and Max Pool layer where all the noises are filtered. The image is then converted to default size of 224x224 in case of VGG1619 classifier and converted into grey scale. Finally, the processed image is sent to an additional layer which is made up Fully Connected layer. The Fully Connected Layer has a SoftMax layer which distinguishes the images as COVID-19 positive or Normal.

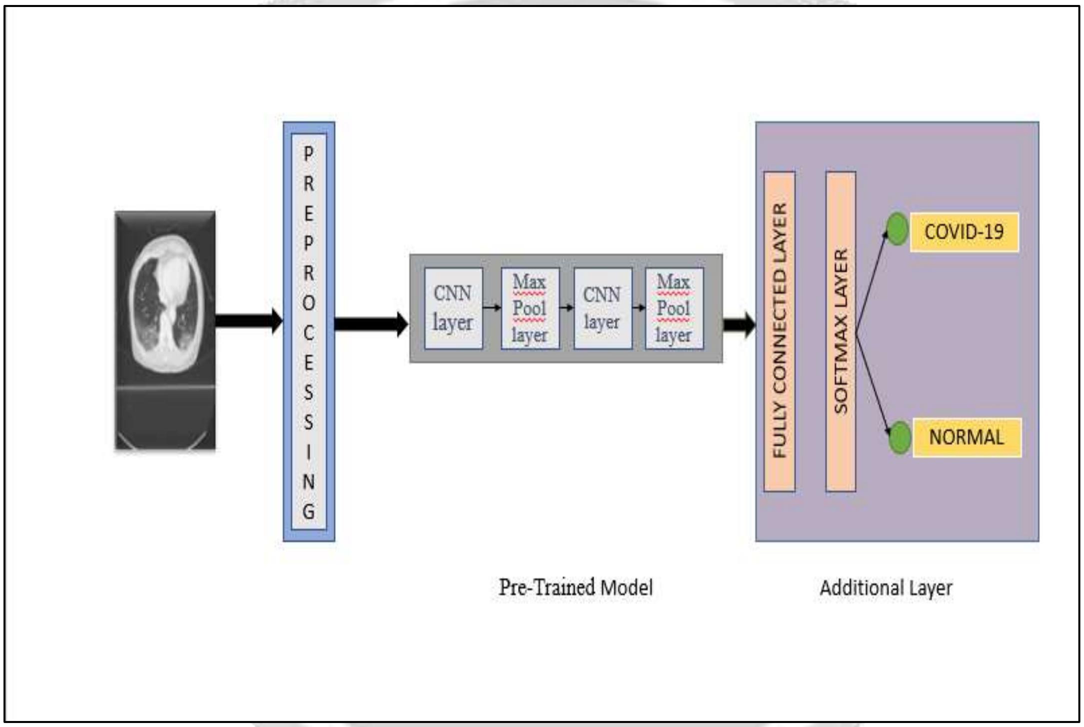


Fig -2: CNN Architecture

IV. RESULTS

CNN Model

The CNN model is trained with chest x-ray, ultrasound and CT scan from dataset. The CNN model is trained with 300 X-Ray images, CT scan images and ultra-scan images in 80:20 ratio.

Basic measures derived from the confusion matrix:

Accuracy (ACC) is calculated as the number of all correct predictions divided by the total number of the dataset. The best accuracy is 1.0, whereas the worst is 0.0. It can also be calculated by 1 – ERR.

Accuracy = (TP+TN)/(P+N)

Precision (PREC) is calculated as the number of correct positive predictions divided by the total number of positive predictions. It is also called positive predictive value (PPV). The best precision is 1.0, whereas the worst is 0.0.

Precision = TP/TP+FP

Error rate (ERR) is calculated as the number of all incorrect predictions divided by the total number of the dataset. The best error rate is 0.0, whereas the worst is 1.0.

Error Rate=(FP+FN)/(P+N)

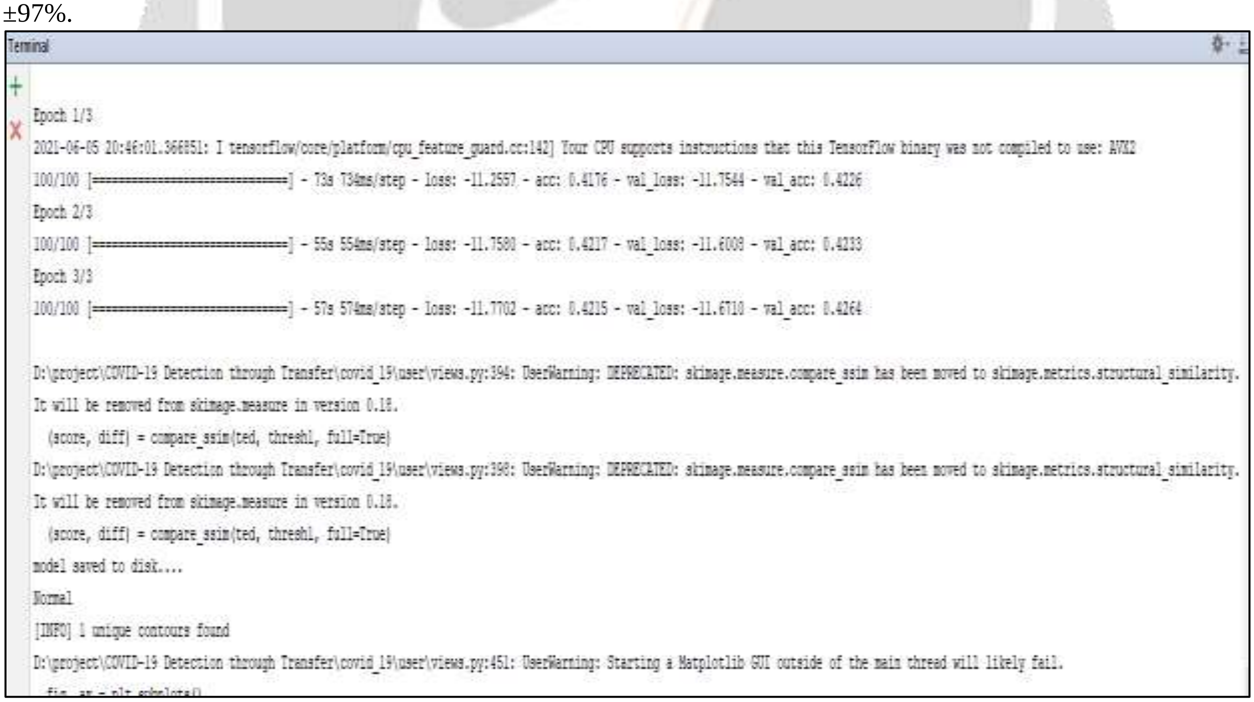
False positive rate (FPR) is calculated as the number of incorrect positive predictions divided by the total number of negatives. The best false positive rate is 0.0 whereas the worst is 1.0. It can also be calculated as 1 – specificity.

FP= FP/TN+FP

Sensitivity = $\frac{TP}{TP+FN}$

F1 Score = $\frac{2 \times \text{Sensitivity} \times \text{Precision}}{\text{Sensitivity} + \text{Precision}}$

In this, we had presented a method that could screen COVID-19 fully automatically by CNN. The model was trained on X- ray, CT scan and ultrasound images of COVID-19 and normal. We have obtained the best performance as a classification accuracy of more than 98%. We have set the training steps to 100, which is sufficient to generate sufficient outcomes. Training accuracy increased as training proceeds after 100 iterations, the final test accuracy was ±97%.



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Terminal
Epoch 1/3
2021-06-05 20:46:01.366851: I tensorflow/core/platform/cpu_feature_guard.cc:142] Your CPU supports instructions that this TensorFlow binary was not compiled to use: AVX2
100/100 [==============================] - 73s 734ms/step - loss: -11.2557 - acc: 0.4176 - val_loss: -11.7544 - val_acc: 0.4226
Epoch 2/3
100/100 [==============================] - 55s 554ms/step - loss: -11.7580 - acc: 0.4217 - val_loss: -11.6008 - val_acc: 0.4233
Epoch 3/3
100/100 [==============================] - 57s 574ms/step - loss: -11.7702 - acc: 0.4215 - val_loss: -11.6710 - val_acc: 0.4264

D:\project\COVID-19 Detection through Transfer\covid_19\user\views.py:394: UserWarning: DEPRECATED: skimage.measure.compare_ssim has been moved to skimage.metrics.structural_similarity.
It will be removed from skimage.measure in version 0.18.
  (score, diff) = compare_ssim(ted, threshl, full=True)
D:\project\COVID-19 Detection through Transfer\covid_19\user\views.py:398: UserWarning: DEPRECATED: skimage.measure.compare_ssim has been moved to skimage.metrics.structural_similarity.
It will be removed from skimage.measure in version 0.18.
  (score, diff) = compare_ssim(ted, threshl, full=True)
model saved to disk....
Normal
[INFO] 1 unique contours found
D:\project\COVID-19 Detection through Transfer\covid_19\user\views.py:451: UserWarning: Starting a Matplotlib GUI outside of the main thread will likely fail.
```

Fig -3: Result obtained by testing the Image

The Figure shows the results when the sample test image was taken to predict the image or classify the image into Covid or normal. The result will be displayed on the application.

Fig -4: Result obtained by testing the Image.

The CNN model generates the result of either Covid Positive or Covid Negative automatically.
The models is trained on all the three sections of X-Ray, Ultrasound and CT Scan images of covid, healthy as well as viral pneumonia patients. We have obtained an accuracy of _97%.

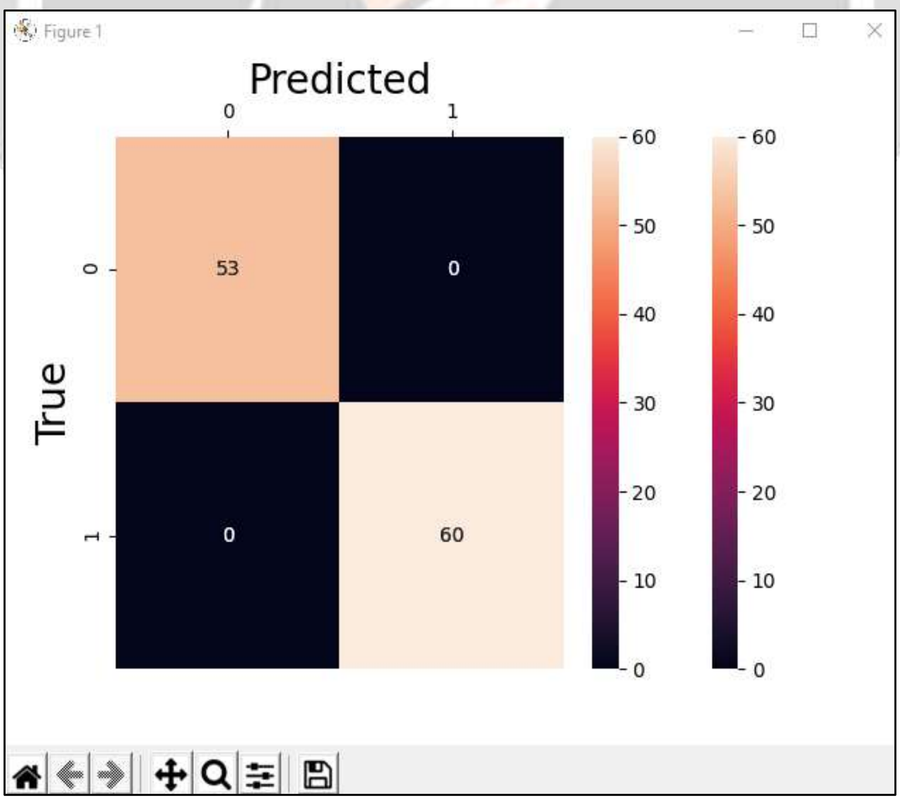

Fig -5: Confusion Matrix

V. CONCLUSION

Covid-19 pandemic has affected the health of people globally. The doctors and nurses have been tirelessly working for the lives of the patients in this pandemic. Our aim is to provide a helping hand through technology such as CNN that is not only affordable but is also quicker. CNN model is efficient in recognizing patterns and image processing because of its features such as simplified architecture, reduced training variables and is compliant. The main benefit of CNN is its ability to automatically recognize significant features without human intervention. Among the three multimodal imaging methods, Ultrasound provides more accuracy and is cheaper and efficient in comparison to X-Ray and CT scan.

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