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A Novel Deep Learning Application To Diagnose Delta Corona Virus

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ABSTRACT

A widely mutated deadly virus called coronaviruses affrighted the global civilizationin 2019. The pandemic brought on by this virus is frightening the human's race severely. Many organizations and individuals are working on best to provide a way to test-based illness prediction. As the suffered individual is getting having lungs infection at first before any severe spread of infection. In our work, we are proposing a novel deep learning based covid delta variant model for early detection of COVID-19 Disease Detection along with an interactive user interface. For disease prediction we are using X-ray Images and classifying whether a person is suffering from covid-19 or not, based on chest x-ray images of that person. The accuracy received is 99.45% with validation loss of 0.0774.

Key words: CNN, X-Ray, Covid-19, Delta variant detector, OpenCV, ReLU, softmax

1. INTRODUCTION

Deep learning is one of the best practice useful to predict the severity of many diseases such asfracture, Urinary Tract Infections, Stomach Infections, Liver and Kidney Infections, etc. Sameway, this area is being explored my many researchers for early diagnosis of a life taking virus,Covid 19. Image classification is new methodology for early detection of Covid 19. Early detection leads to less severity of infection and hence less number of deaths. X-Ray images, CT images to detect and predict one's health is a new and successful way of medical diagnosis.As the patients are increasing exponentially globally[1], it is hard to analyse all the scans manually, therefore an advance AI based system that can automatically detect and predict the severity of this infection is need of the hour.

The new variants are getting detected every other day, keeping a few common symptoms suchas nausea, cold, fever and infection of lungs. Newly detected delta variant has claimed deaths of 270,000 individuals in three months, more than twice the number we saw in the entire year of 2019 and mid of 2020[2]. The Delta strain is different. It has a higher affinity for lung tissues than other strains, making it more lethal. But that was not the only thing that made it different. People were returning negative RT-PCR tests while being infected with COVID, which was subsequently discovered after they had their chest X-Rays diagnosed by a doctor.

In this work, we are using x-ray scans, CT scans and classifying whether the image is of a healthy individual or not. In case it is found be of an infected one, the model tries to predict whether the individual is suffering from pneumonia or Covid. If found to be of a Covid, the model also generates a severity score to mark the intensity of infection, helping the doctors to right medications and cure. The CNN machine learning module is core of this work. The proposed model is purely based upon deep learning algorithms and functions that can train itselfn number of times as it will take new data from the user and perform all the mentioned.

2. RELATED WORK

COVID-19 is highly communicable viral infection. The sickness is contagious infecting the human race at very high pace. For a number of image processing applications, including imageanalysis [3, 4], image classification [5], and image segmentation [6], ML has shown great performance. Using classifiers like SVM [7], image classification is accomplished by first

extracting the important features from the images using a descriptor (for example, SIFT [8] and image moment [9]). Deep neural network-based approaches [10] offer high performance in categorizing the images according to the extracted characteristics, in contrast to handcrafted features. Several initiatives used machine learning-based techniques to categories the chest x- ray pictures into COVID-19 patient class or normal case class in accordance with the characteristics of ML. [11]

To identify Pneumonia disease in chest X-ray pictures, Parveen Netal. utilised an unsupervisedclassification technique called fuzzy c-means [12]. It was found that the unsupervised fuzzy C- means approach outperformed other methods including DWT, WFT, and WPT in terms of identification outcomes. To detect the existence of respiratory disease clouds in chest X-rays, Abhishek Sharma et al. suggested employing image processing techniques [13]. To detect the existence of pneumonia, they suggested calculating the area of the healthy respiratoryorgan region in relation to the overall respiratory organ region. Convolutional Neural Networkswere employed by Khan Maseeh Shuaib et al. to detect pneumonia from X-ray pictures [14] and the classification accuracy was 84%. For the automatic diagnosis of the coronavirus, Apostolopoulos et al. collected a dataset of X-ray pictures from patients with COVID-19, respiratory ailments, and other diseases from public archives [15]. They used transfer learningwith CNN for the purpose of identifying any anomalies in datasets of medical X-ray images, and they achieved 96% accuracy. They concluded that Deep Learning can successfully identify important, distinctive biomarkers linked to Coronavirus from X-ray pictures.

A recent base study on AI for automatic categorization of Xrays utilizing the biggeropen source CT dataset is reported in here. For the classification job, the retrained DenseNet was used in many studies. For retraining the previously taught deep- learning model with fresh picture data, these authors used transfer learning and data augmentation. The theory behind transfer learning is that by using a produced model as the foundation for training a new model with a different objective, it can eliminate the requirement for gathering a huge amount of training data. A sizable collection of chest X-ray pictures was used for the data augmentation. In order to boost performance and the deep-learning model's capacity to generalise the power of classification by becoming accustomed to samples of high variance, picture data augmentation aims to increase the size of the training dataset with plausible examples.

It should be emphasized that the CT datasets utilized in the investigations described in.[16,17,18, and 19] are not accessible to the public. This work presents a thorough analysis of 16 pretrained CNNs for COVID-19 classification utilizing a publicly available CT database. Based on the training and testing of the ImageNet database [20], these pretrained CNNs exhibit a range of computational complexity and accuracy. In terms of the simplicity ofboth data preparation and software implementation for battling the pandemic, the findings of this inquiry would make it easier to deploy AI-assisted solutions to various hospitals and pathological centers in a timely manner.

For proposed model testing, we have used the finest dataset that is currently available with thespecific intent of developing a system to identify the covid-19 illness. We have folded the dataset as precisely as feasible to maximize the accuracy of the model that will be produced. The precision of the model was first insufficient to anticipate the outcome, but subsequently, by increasing the number of steps each epoch, we overcame that challenge. Nowwas the turn to develop the model in that way, that it can learn from the previous datasets and then keep on learning without losing its integrity and accuracy. For the outcome analysis, we have also plotted some graphs and sea map, with accuracy checking by confusion matrix.

3. Methodology

In our work, we have collected different types of infected and normal x-ray images are gatheredand then grouped on the basis respective classes. Once the dataset is structured then, the cleaning of the data and the major phase of the model starts and those are creating, training and testing the model. Creating the model is the most important task as the structure of the model will decide the behavior of the whole system. The work aims to diagnose Chest X-Rayscans for COVID-19 and Viral Pneumonia. Whole system follows the below structuredarchitecture showcased in Figure 01 from creating a model to produce the output as predictionand so on.

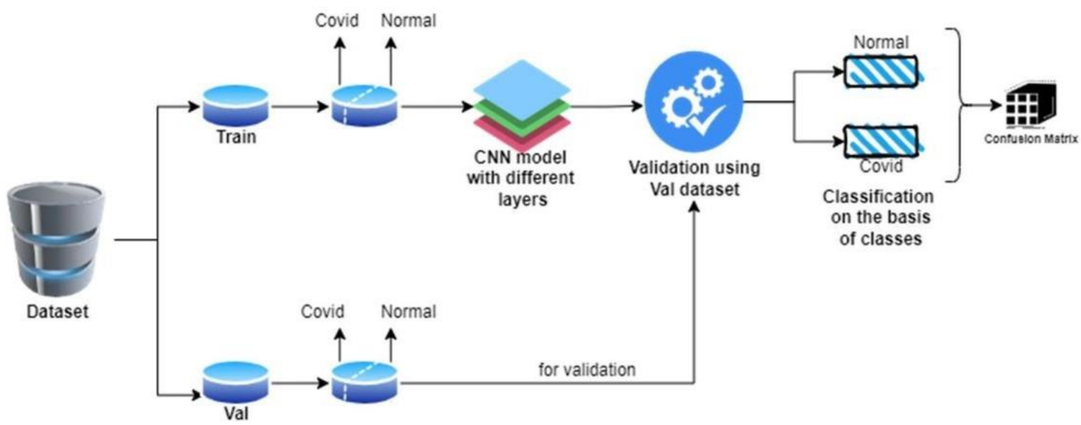

Figure 01: Delta Infection Detector Model Architecture

There are three major components of this project, first a convolutional Neural Network that is trained to classify Chest X-Rays as COVID, Viral Pneumonia, or Normal, second an API that could take in Image URL as a parameter and utilize the trained model to make predictions. Andlastly, an Interactive UI on which users can directly upload their Chest X-Rays and get a live diagnosis in less than a second. After creating the model, training of the model will begin whichwill take images as their feed and then will learn from it. Training and validation classes are also generated to classify the outcome as diseased or normal. And then to produce the result wecreate two lists to plot some charts and created a confusion matrix.

a) Building the Model

(i) Collection of Data

Data related to the healthcare industry is not openly accessible. We searched, selected, and merged two relevant datasets on Kaggle. There were 66 test photos and 251 training images in the first dataset [21]. The second dataset had 119 test images, as well as 1704 training photos [22]. We have 185 Test Images and 1955 Training Images in the combined dataset.

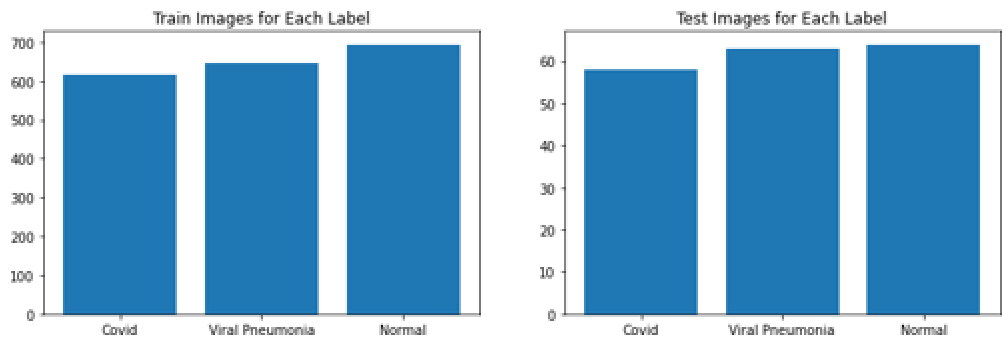

Figure 02: Distribution of collected dataset

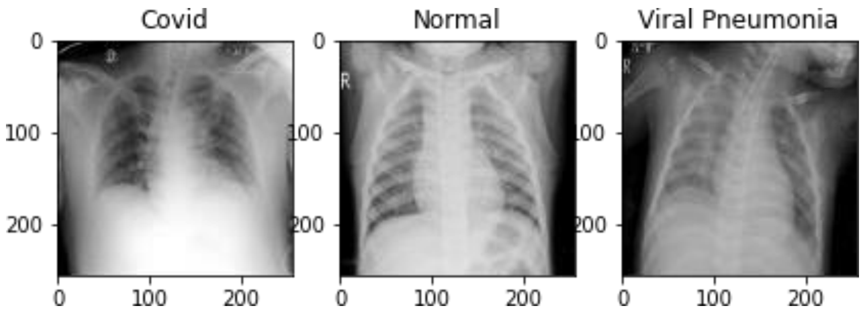

Figure 03: Sample

DatasetData Sample is shown in Figure 03.

(ii) Reading and Pre-Processing of Collected Data

Utilizing OpenCV, we are reading the images from the disk, resizing them to 256 x 256 pixels(so that each image is of the same dimension) and finally dividing each pixel by 255 for normalizing them. The labels assigned to the images are as COVID – 0, Viral Pneumonia – 1, Normal – 2.

(iii) Data Augmentation

Augmentation is the process of creating new training samples by altering the available data. It not only increases the number of samples for training the model but also prevents the model from overfitting the training data since it makes relevant features in the image location invariant.

Although there are various ways of doing so like random zoom, altering brightness, rotating theimages, most of it does not make sense for health-related data as the real-world data is almost always of high quality and properly aligned. So, we only used one type of Image Augmentation in this Model: Horizontal Flip Now, even if someone tries to classify horizontally flipped images,we can expect to get correct predictions. After applying image augmentation, we have 3910 training samples in total, s sample is shown in Figure 04.

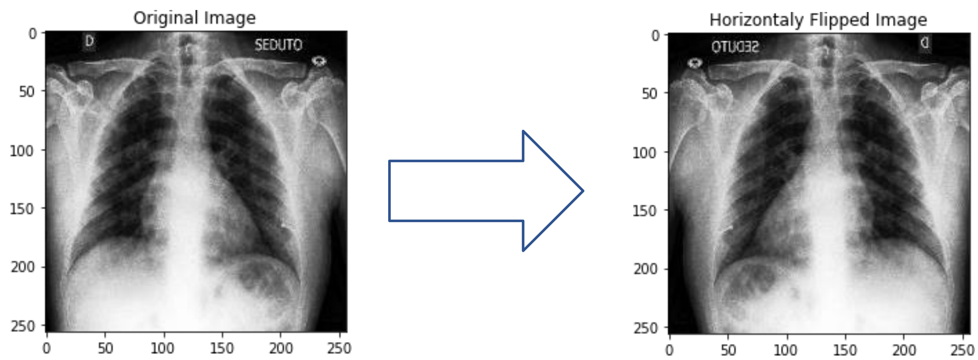

Figure 04: Augmented Images of Dataset

(iv) Data Splitting

We used 15% of the data (587 samples) for validation and the rest 85% (3323 samples) for training the model. The split was done in a way that the samples are shuffled, the ratio of each class is maintained (stratified). Tog et the same samples every time we randomly split the data.

(v) Model Designing

We created a sequential model with four dense layers and five convolutional layers. With a 2x2 kernel size and 32 filters, the first layer got started. At each subsequent layer, the number of filters doubles, while the kernel is increased by 1. After the convolutional layers, we added a few Max Pooling Layers to prevent over-fitting and lower computational costs. Convolutional layer output is flattened and transferred to dense layer. In the first Dense layer, we started with 512 neurons and cut that number in half across the following two Dense layers. Additionally, some Dropout Layers were added to the model to haphazardly ignore part of the neurons and lessen over-fitting. Except for the output layer, we used ReLU activation in all layers to lower computing costs and add non-linearity. The Output Layer, which includes SoftMax activation function and 3 neurons (one for each class), was then built.

(vi) Model Training

The model was compiled with 'sparse_categorical_crossentropy' loss, Adam optimizer, and Accuracy as metrics. The Early-Stopping-Policy was set to monitor validation loss and check ifit does not decrease in 20 continuous epochs, stopping the training process. The Check-Pointer was set up to save the model whenever the validation loss improved. The model was set to be trained for 100 epochs, but it was terminated at the 79th epoch. It was last saved on the 59th epoch recording a validation accuracy of 99% and validation loss of 0.0774.

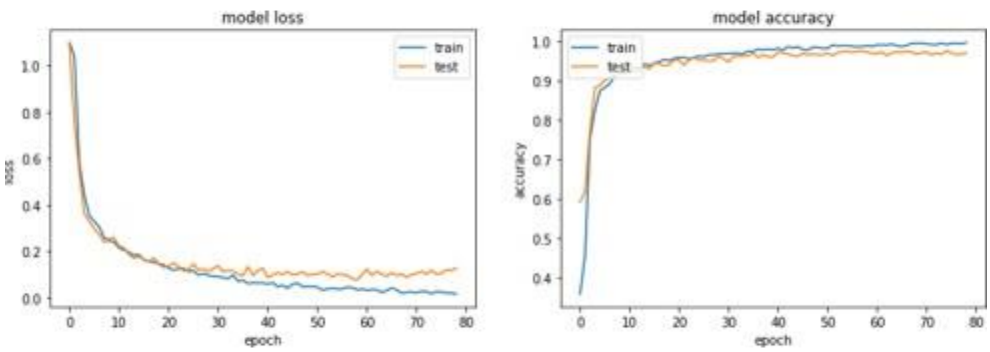

Figure 05: Proposed Model Accuracy and Loss Plot

b) Building the API

FastAPI is a modern, fast (high-peífoímance), web framewoík foí building APIs with Python 3.6+.

There are two routes in it –

(i) '/' – This is a classify URL route that can be utilized by sending a post request on it with a JSON file containing the URL of the image to be diagnosed as a parameter. This can be very useful if we are using different technologies which are incompatiblewith each other for example if we are developing an app using

Flutter, we can utilizethe trained model just by sending a post request on this URL.9

(ii) '/predict_image' – This is the route on which we can directly send the image for diagnosis. This can be useful in case we just want to try out the API without writing the code.

The FastAPI also features an in-built UI (Swagger UI) that can be accessed by switching to the '/docs' route. The API is deployed on Heroku.

c) Builder User Interface

The UI was built using Streamlit and features an Upload Image button using which, users can upload their chest MRI scans and get real-time results in less than a second. After developing theUI, we deployed it on Streamlit Cloud for public usage.

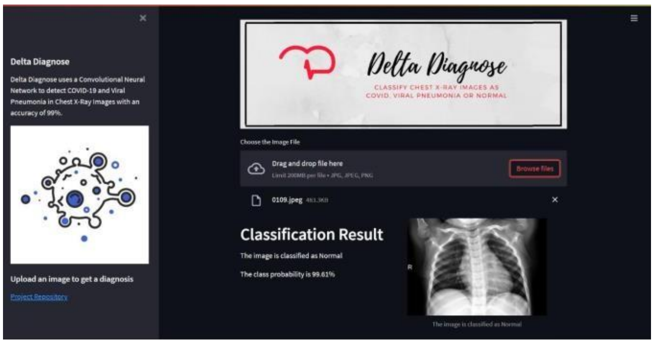

Figure 06: Application Interface for Delta Infection Detector

4. RESULTS

Our model was able to classify 99% of the test samples correctly. Precision and Recall are also good for all the classes. The confusion matrix is showcased in Figure 07.

	precision	recall	f1-score	support
0	1.00	0.98	0.99	58
1	1.00	1.00	1.00	63
2	0.98	1.00	0.99	64
accuracy			0.99	185
macro avg	0.99	0.99	0.99	185
weighted avg	0.99	0.99	0.99	185

Figure 07: Confusion Matrix of Proposed Model

Glimpse of infected and normal images as claasified by the proposed model is given in Figure 08.

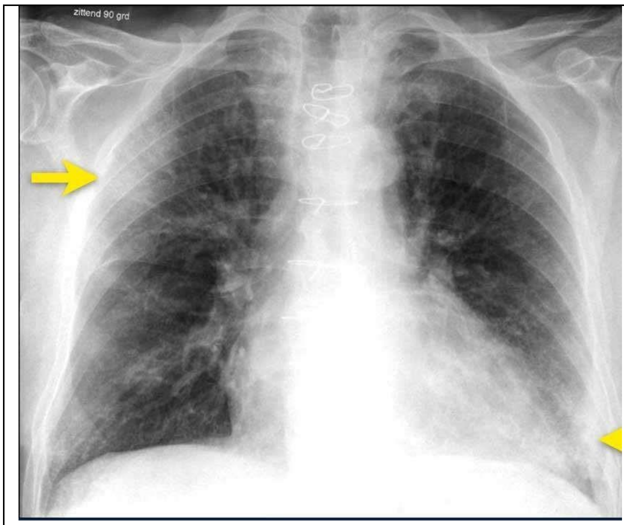	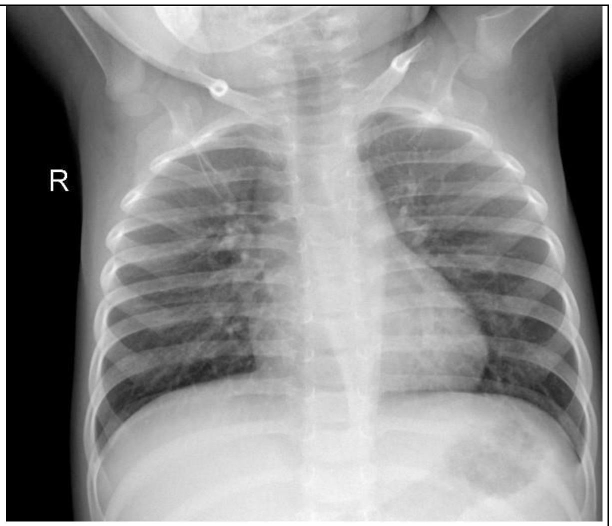
Covid 19 Infected Image	Normal Image

Figure 08: Classification of Images in Infected or Normal

5. CONCLUSIONS

Covid-19 as well as its variants should be rigrously detected within timelines. While the situationhas improved for the time being, regular and thorough health checks are still required. The detecting mechanism was only made with the intention of increasing the likelihood of an accurateforecast. The variety in illness can be detected because different virus variants exhibit various behaviours in their natural state. Our model was able to classify 99.45% of the test samples correctly. Precision and Recall are also good for all the classes. The visualisation aided application wherein user can easily upload and check the intensity of infection is also provided. All governmental and corporate sectors work to improve people's lives in order to keep the situation under control and avoid the scenario that occurred in 2019, therefore we should also contribute in any manner that is humanly feasible. We have tried to implement and predict the outcome as much correctly as possible to help the community and provide our society with someaid.

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