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Covid19 Detection and Severity Analysis Using Chest Computed Tomography

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ABSTRACT: From the onset of its discovery, the SARS COV2 virus has pushed the world of science to innovate and discover new ways to tackle it. Several scholars have been working tirelessly to improve the condition for everyone. This paper intends to provide simpler ways to detect COVID19 in patients using deep learning methods on CT images, as well as perform segmentation on the COVID19 infected images to diagnose the severity of the disease. We have built a custom model and compared it to the pre-existing standard models VGG16 and Alexnet. Our model displayed the highest accuracy of 97.65% as compared to the standard ones of 92.97% and 93.50% respectively. Furthermore, we used U-net architecture to segment the COVID19 infected lung areas in order to diagnose the severity of the disease. It has shown an accuracy of 83%. We imported a dataset from Kaggle API directly to implement it in our model.

KEYWORDS- COVID19, Deep learning, CT images, Segmentation, Ground glass opacity, Convolutional neural network

I. INTRODUCTION

SARS-CoV-2, a virus, was discovered in Wuhan, China, in the year 2019. The resulting pneumonia was given the name COVID-19. With a tremendously high fatality rate, the globe was engulfed in a pandemic as a result of the virus's rapid and widespread transmission. Cough, pulmonary inflammation, and fever are some of the clinical signs, which might worsen the Acute Respiratory Distress Syndrome.

Due to the lengthy time necessary for diagnosis, standard RT-PCR (Reverse transcription polymerase chain reaction) diagnostics have proven to be ineffective. They've also been chastised for having a high false-negative rate and an efficiency rate of only 70-80%[1]. Furthermore, PCR testing is only effective if the virus is present in the upper respiratory tract. With a sensitivity of 95.38 percent, Computed Tomography significantly exceeds RT PCR assays. They can diagnose patients at acute stages of the illness. The proportion of ground-glass opacity in Computed Tomography images can also be used to determine the severity of infection[2].

A Ground Glass Opacity(GGO) can be defined as a region of enhanced attenuation in the lung with preserved bronchial and vascular patterns. In order to achieve accurate and rapid diagnosis of COVID-19 suspected cases, and to locate the infected areas in CT images, we designed a custom based COVID-19 rapid diagnosis and classification model from scratch. The model classifies the covid images from the non-covid ones. We have also compared our model with the standard models (VGG16 and Alexnet). Our model displayed an accuracy of 97.65% while VGG16 showed an accuracy of 92.97% and Alexnet, an accuracy of 93.5%. We further used U-net architecture to segment the GGO infected areas in COVID19 patients to analyse its severity. We applied the Contrast Limited Adaptive Histogram Equalisation (CLAHE) method on the images to take care of its over-amplification.

II. LITERATURE SURVEY

A. Deep learning methods

Khushi Janani and her colleagues used transfer learning to extract feature vectors in [3]. They compared their model to conventional models such as VGG16, L InceptionV3, and others, and found that only VGG16 had better accuracy than theirs. Reduce on plateau, cyclic learning rate and constant learning rate are some of the learning policies that were explored after Talha Anwar and Seema Zakib performed data augmentation on their dataset to expand its size in [4]. Sertan Serte an AI approach in [5] that uses the ResNet-50 deep learning model to predict COVID-19 on each CT image in a 3D CT scan. COVID-19 may be detected on CT scans with a 96 percent accuracy using the suggested deep learning algorithm. The proposed technique, on the other hand, needs the execution of a large number of ResNet-50 designs in parallel, which is restricted by the available hardware memory capacity. Wentao et al. investigated the performance of several pre trained models on CT testing and discovered that larger, out-of-field datasets improve the models' testing power in [6].

B. Segmentation methods

Yazan Qiblawey and his colleagues, in [7] devised a cascaded approach for segmenting lungs, detecting, localising, and quantifying infection. They employed the Feature Pyramid Network with several backbone structures such as DenseNet and ResNet to conduct encoder-decoder in CNN. Shikha et al. in [8] used a noncontrast chest CT as their starting point and then segment the lesions, lungs, and lobes in three dimensions. To partition infected tissue regions in CT lung images, Adnan Sood and Iyad Hatem evaluated U-Net and SegNet models in [9]. Their findings showed that all the other approaches were outperformed by Segnet in categorising infected/non infected tissues but the U-NET performed better as a multi-class segmenter. Amine Anyar and her colleagues' paper in [10] based on classification and segmentation of covid19 in patients, different datasets are used to complete three learning tasks: segmentation, classification, and reconstruction. S.N Kumar et al. published a paper for COVID19 on ROI extraction from CT images, proposing rapid fuzzy means clustering and preprocessing with a median filter in [11].

III. WORKING

The proposed architecture consists of the diagnosis models which predict if the lung is infected or not. Once the model detects infection in the lung, we further proceed to the segmentation model to identify the infected areas of lungs.

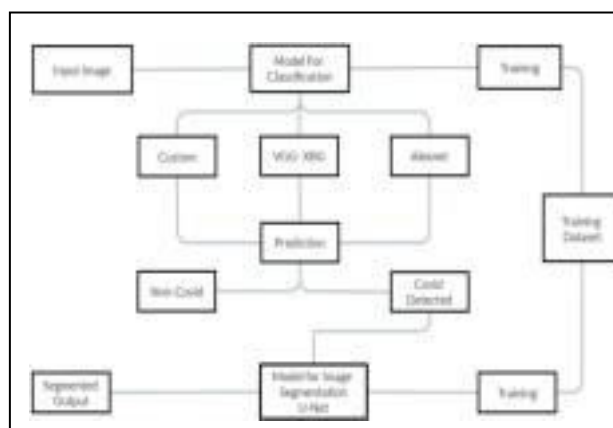


Fig.1 Overview

A. Diagnosis model

Deep learning is a subset of artificial neural networks that uses algorithms that are inspired by how the brain works. Using many convolutional filters, Deep Learning does feature extraction on its own. A number of convolutional layers, activation functions, pooling approaches, and other factors are used to create different deep learning architectures. In the COVID-19 detection, after preprocessing the input images, Convolutional neural networks are used to identify GGOs and confirm COVID-19.

The dataset used for this diagnosis model has been directly imported from “Kaggle COVID-19 database”. Similar datasets for related work are also available in Github repositories. Our dataset comprises 2546 CT scan images

collected from 1301 COVID patients and 1245 non-COVID persons.

B. VGG-16 with XGBoost

For our image classification tasks, we employed transfer learning. The weights in the re used layer are utilised as a starting point for the training process when transfer learning is implemented. Because the weights learned in the lower layers are more generic characteristics that are usually relevant to most other tasks, the model at the end may normally perform better in terms of generalisation[12]. The VGG model is the most widely used deep learning architecture. We recommend employing VGG16 without the higher layer to create a deep CNN with transfer learning. VGG16's top layer was replaced by the XGBoost classifier. The type of learning transfer used in this model is inductive transfer learning utilising the ImageNet weighted VGG16 model. The VGG16 model's weight, which was utilised to extract features from both covid and non-covid images.

C. Alexnet

AlexNet is one of the Convolutional Neural Network versions, commonly known as a Deep Convolutional Neural Network (DCN). Alexnet consists of eight main layers with Five convolutional layers and three fully connected layers.[13][14]At the end it is enclosed with sigmoid or softmax layer, which is application specific and we used sigmoid as it shows better classification accuracy. Convolutional filters and a nonlinear activation function ReLU are used in each convolutional layer. The usual input size used for alexnet is $224 \times 224 \times 3$ and in some rare cases with padding $277 \times 227 \times 3$ is used. Hyperparameter tuning can be performed to improve the training results. However, we will not utilise the pre-trained weights in this paper and instead define the CNN according to the recommended design.

D. Custom model

There are a number of popular pre-trained models available that can help overcome sampling problems sincethey have previously been trained on a large number of images and can detect a wide range of characteristics. When interpreting the differences between hundreds or thousands of classes, these models generally have complicated architecture. Because the pre-trained model might overfit the data, the complexity that provides prediction capability for a range of items can be a disadvantage for application specific problem statements. The following steps were carried out in implementing our custom model:

- **Image Pre-Processing:** When working with image data, image pre-processing is the first and most important stage. We just resize all of the images to the appropriate size (in our scenario, $227 \times 227 \times 3$). We went through every image in the folder, both infected and non-infected, according to the directory structure of our dataset and re-sized them accordingly.
- **Design Model Architecture :** We attempted to build a model from scratch having known we needed a binary-classification model. We proceeded to the implementation part and realised we achieved decent accuracy but not good enough as previously discussed standard models. So we took retrospective measures and decided to re-build and customise the architecture for better. This time we had a clear idea that the feature extraction part has to be improved in order to improve accuracy of the model.

Several convolutional and pooling layers make up a Convolutional Neural Network. Five Conv2D and MaxPooling layers were added. The initial parameter of the Conv2D layer is where we need to study a lot to get the best model possible. The model architecture is shown in fig**. We replaced the softmax from the primitive model we built with sigmoid. Most of the CNN models employ Softmax for multi-classification and Sigmoid for binary classification.

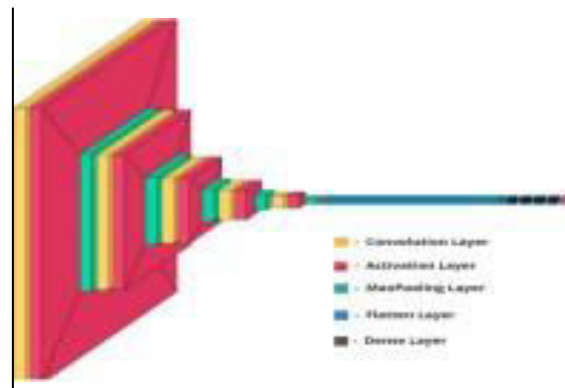


Fig.2 Custom CNN Architecture

E. Segmentation Model

In order to make a prognosis of illness progression, segmentation is an important stage in deep learning based COVID19 image processing and its analysis. It distinguishes the regions of interest (ROIs) in CT images, such as the lung, lobes, bronchopulmonary segments, and infected regions or lesions, for further assessment and quantification.

The dataset we used for our segmentation model is composed of 20 CT scans of patients diagnosed with COVID-19 and their segmentations of lungs and infections made by experts. It was imported from GitHub COVID Chest CT scan dataset.

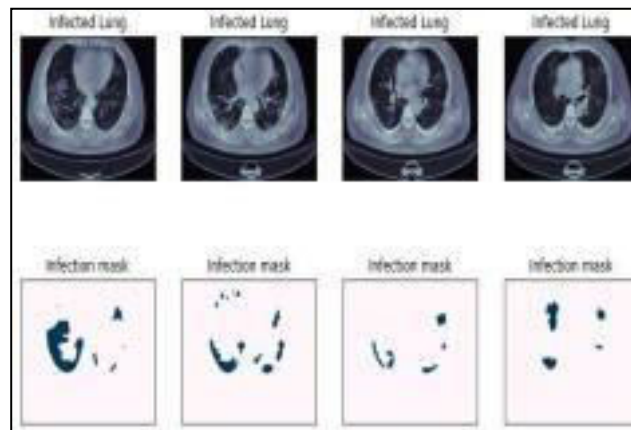


Fig3

F. U2 Net

U-NET was created with the intention of comprehending and segmenting medical images. It is a significant architecture in the medical imaging automation society and has a myriad of applications in the sector. This network's design is divided into two parts: contractive and expansive. Following the ReLU layers, the contracting path consists of a series of convolutional patches with size 3×3 filters and unity strides in both directions. This path extracts the input's essential features and returns a feature vector of a certain length. The subsequent route extracts data from the contractive path by copying and cropping, as well as from the feature vector using up convolutions, and forms an output segmentation map via a series of operations. The operation that connects the first and second pathways is a crucial part of this system. This connection enables the network to obtain very precise data from the contractive path, resulting in a segmentation mask that is as near to the intended output as feasible.



Fig.4 U-net Architecture

IV. RESULTS AND DISCUSSIONS

We have compared the accuracy, F1 Score, recall and precision of the three models, as well as their confusionmatrix. The results are displayed below:

A. Confusion Matrix

A confusion matrix is a table that displays the performance of a classification method. It is used to illustrate andtotal the performance of a classification algorithm.

CNN Models	True Positive	True Negative	False Positive	False Negative
Custom Model	59	66	0	3
VGG 16 XGB	56	63	3	6
AlexNet	58	59	0	8

Table 1. Confusion Matrix Results

B. Accuracy

The percentage ratio of correct predictions made by our model is called accuracy. It's calculated as the number of right predictions divided by the total number of predictions.

$$Accuracy = \frac{2222 + 2222}{2222 + 2222 + 2222 + 2222}$$



Fig.5 Model Accuracies

C. F1 score

The F1-score is a harmonic average of Precision and Recall, resulting in a composite representation of the two measurements. It's at its finest when Precision matches Recall. When we try to improve the precision of our model, the recall drops, and vice versa. The F1-score is a single value that incorporates both trends.

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

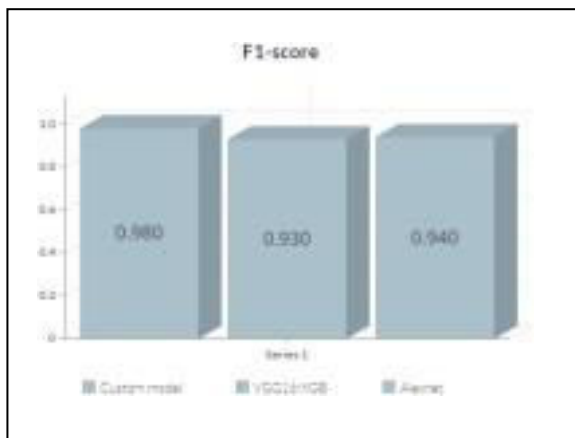


Fig.6 F1 Scores

D. Precision

Precision is a metric that evaluates how accurate a model is at categorising a sample as positive. The ratio of True Positive to True Positive plus False Positive is used to compute it.

$$Precision = \frac{TP}{TP + FP}$$



CNN Models	0	1
Custom Model	1	0.96
VGG16-XGB	0.90	0.95
Alexnet	0.88	1

Table 2. Precision

E. Recall

Recall is the model's ability measured to identify Positive samples. Positive samples are identified in greater numbers when the recall is larger. The ratio of True Positive to True Positive + False Negative is used to compute it.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

CNN Models	0	1
Custom Model	0.95	1
VGG16-XGB	0.90	0.95
Alexnet	1	0.88

Table 3. Recall

F. Segmentation Results

Once the Diagnosis model detects COVID19 in the chest CT it was further taken into U-net for infection segmentation. Our U-net model performed well and has shown an accuracy of 83%.

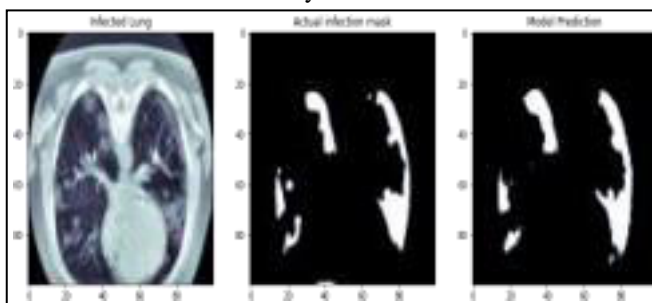


Fig.7.a

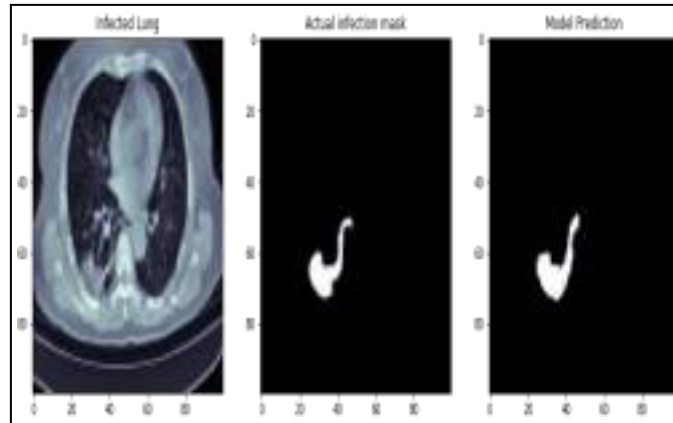


Fig. 7.b Figure 7.a & 7.b Shows the infected lung as identified by our diagnosis model and actual infection mask and the prediction of the Segmentation model.

V. CONCLUSION

Identification of GGO is an integral part of scanning the lungs for COVID-19 in order to arrive at proper diagnostic conclusions. Automated identification of GGO is still a very challenging issue for the healthcare industry. In this paper, we have not only built a custom model for detection of COVID

19 in patients using deep learning, but also built a U net based architectural model that analyses the COVID-19 infection in lungs so as to give a better idea of its severity. This helps the doctor and eliminates the errors that could have occurred in manual examination. Our detection model has shown an accuracy of 97.2% which is higher than both the VGG16 and Alexnet models and our U-net model has shown an appreciable accuracy of 83%.

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