COVID-19 Diagnosis with HRCT Images Using Deep Transfer Learning

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2022 First International Conference on Artificial Intelligence Trends and Pattern Recognition (ICAITPR) | 978-1-6654-2521-6/22/$31.00 ©2022 IEEE | DOI: 10.1109/ICAITPR51569.2022.9844195

***Abstract*—High-resolution computed tomography (HRCT) is a way of diagnosing, in which x-rays are used to acquire the high resolution images. It is one of the types of Computed Tomography(CT) which is more clear and accurate in giving precise results. The HRCT scan covers the whole lung tissue which helps to find the cause of any abnormalities in scanned images. The present study is undertaken to investigate COVID-19 disease on HRCT images with Deep Transfer Learning models. In this paper, we are proposing Deep Learning model on HRCT Images for predicting whether a patient is affected or not. The Proposed model is an automatic classification of images by considering Mobile Net, Inception Net, VGG16, Resnet50, CNN deep learning models. The results are obtained from Inception Net with classification mean accuracy of 99%. Our model demonstrates the use of InceptionNet deep transfer learning model for diagnosing Covid-19 as an alternate way of testing the infection.**

***Index Terms*—HRCT, COVID-19 Data set, MobileNet, InceptionNet, VGG16, Resnet50, CNN**

I. Introduction

COVID-19 is an infection which is caused by SARS-CoV-2. The first covid-19 case recorded in 2019 in Wuhan city, China, because of the fast spreading nature of infect covid-19 declared as global pandemic by World Health Organization (WHO) [1]. The symptoms to identify this infection are almost similar to seasonal flu and the common symptoms includes shortness of breath, fever, cold, muscle pain, loosing smell and sore throat. In most cases patients are asymptotic. Since the inception of pandemic many researchers working on developing systems to help doctors in fast and accurate diagnosis, using data from radiographic images like CT scan images as well as HRCT images. India is at second place with number of confirmed cases in the world with 34,666,241 reported cases of COVID-19 infection as on 07.12.2021. [2].

During the early days of pandemic testing samples need to be examined in virology lab for diagnosing covid-19 . Entire world did suffer with the shortage of testing and cases increased exponentially as most patients were either asymptotic or not being tested due to lack of testing kits. Doctors also suggested use of radiographic images like x-ray and CT scan for checking whether the covid-19 infection present in lungs or not. Many countries used radiographic images for diagnosing COVID-19 where testing kits are short. Research on radiographic image based COVID-19 can save huge amount of time and money if done properly and results were accurate. [3] [4]. The main objective of diagnosis of HRCT images using transfer leaning is to predict a patient's lungs are infected with covid-19 or they are normal i.e we classify the HRCT image as covid-19 positive image or negative image . There are pros and cons in using transfer learning approach. Transfer learning approach is most effective, accurate and also easy to design and implement, but on flip side we may not develop 100% accurate model which is problem for medical image based diagnosis. A prediction of false negative for a COVID-19 infected patient is most problematic as asymptotic positive patients are the bigger vehicles for spreading pandemic, so a wrong prediction will increase the spreading of pandemic.

This paper focused on comparing different pre trained models which are used as base models for transfer learning to predict the presence of covid-19 infection in a patient chest HRCT image. The models which We used in our work are Mobile Net, Inception Net, VGG16, Resnet50 and traditional CNN. In transfer learning the output layer is removed and is replaced by our fine tuned output predicting layer.The base layers are already pre trained and the weights of these base layers are not updated during the training process on covid-19 dataset [5] . The remaining sections of this paper are Literature review where we underlined the research done previously on radiographic images related to covid-19, Related work which has the process we followed to develop the technique for detecting covid-19 using HRCT images and the Results we obtained after training the models using transfer learning.

II. Literature Review

Currently, Reverse Transcription–Polymerase Chain Reaction(RT-PCR) test is being used to detect covid-19. This is primary and mostly used across globe for covid-19 diagnosis. RT-PCR test used a methodology to find a genome specifically virus RNA in patient sample [15]. But the accuracy of this test is in discussion as its giving considerable number of false negatives . A research work done by Ai T et al. [6], reported that the research carried out on 1014 patients, among them 601 were had a positive result with RT-PCR test, when diagnosis ed with CT-scan 884 of them had positive result, and the sensitivity is 97% in reporting covid-19 in RT-PCR positive cases. And in Ugas-Charcape CF et al. research [7] carried out on 140 pediatrics, reported that patients with positive result of covid-19 on RT-PCR are not having symptoms of ground-glass opacity. But when diagnosis done with chest radiograph (CXR) and/or with CT results shown the presence of ground-glass opacities (ggo), pulmonary vascular engorgement and peribronchial thickening, all these immediate attention and need to be treated in ICU. Hence chest scan also important in most of the cases though the patients were asymptotic of chest illness.

A deep learning model called COVNet developed by Li et al. [8] detects covid-19 in chest CT scans by extracting features from the image. Based on extracted features they classify non-pneumonia lung diseases and community lung diseases. For automatic segmentation of lung infection and quantify their volumetric ratios in lungs Shan et al. [9] developed a deep learning-based model on chest CT scans. Xu et al. . [10] used deep learning based model to classify between influenza-A viral pneumonia and COVID-19 pneumonia and obtained maximum accuracy of 86.7% using CNN model for prediction. Wang et al. [11] Based on the changes in radiographic images of lungs they predicted the covid-19 using deep learning technique, they achieved an accuracy of 89.5% in internal validation with the modified Incepton (M-Inception) model. They shown that from the medical image we can extract features using deep learning and use these features to classify those images for covid-19 prediction, and this prediction showing better results in terms of accuracy than xu's model.

III. Methodology

Our work is carried out in stages such as Data Collection, Data pre-processing and Transfer Learning approach for detecting COVID.

A. HRCT Dataset

In our work we used a data set [5] containing 3840 HRCT images for designing classifier which could give accurate prediction. The data set is containing 2 classes which are labeled as either COVID or Normal, we use this data set for our binary classification. This data set is available in Kaggle site for public use. From the data set we considered total of 2842 training chest radiography HRCT images (1378 COVID affected+ 1464 Normal), 400 images for testing (200 COVID affected +200 Normal),400 images (200 COVID affected + 200 Normal) for validation, this data set is verified by a panel of physicians. In this data set there are collected images of public who are infected with COVID-19 and not infected with COVID-19 but having symptoms, this data set contains images of all age groups and captured without any shrinking to maintain the quality. These images are pre-processed and resized to (224,224). The images for a quick reference shown in "Fig 1","Fig 2".

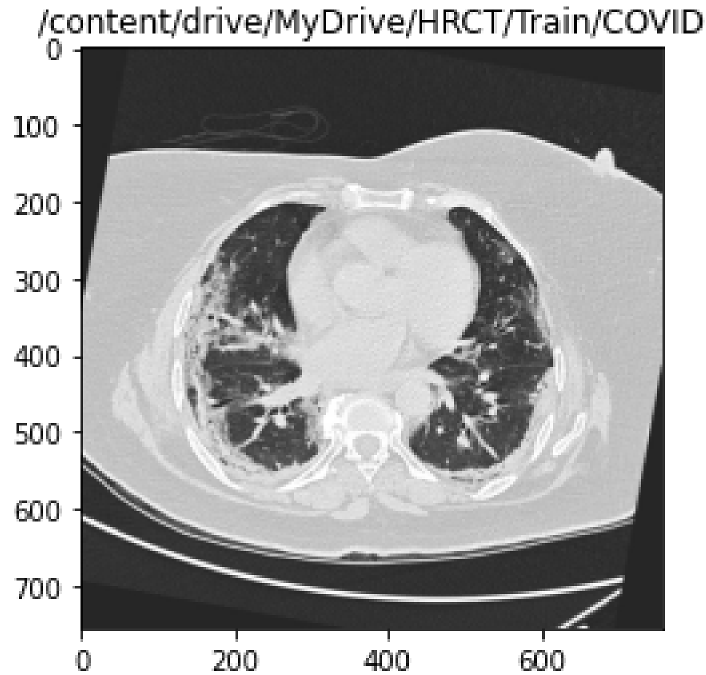

Fig. 1. COVID-19 Image.

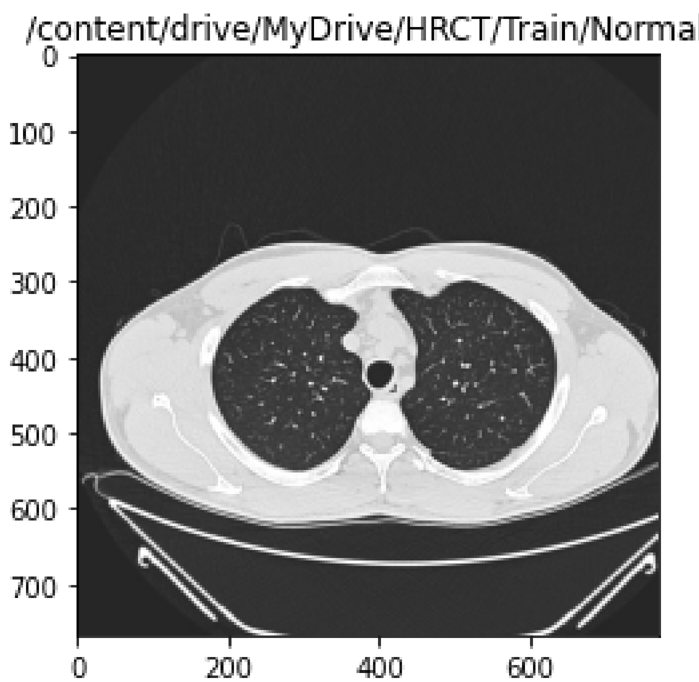

Fig. 2. Normal Image.

B. Data Pre-Processing

In data pre-processing stage images are resized to (224,224) and Gamma corrected on pixel level for image enhancement [12] by

- Converting image from RGB to Gray scale.

- Compute the ratio by using log(mid gray)/log(mean) on the gray scale image.
- Raise the input image value to the power of the ratio.

C. Transfer learning

Transfer Learning uses the the knowledge of an existing deep learning-based model to design a new model. Transfer learning commonly uses two approaches.

- Develop own model.
- Use a pre-trained model.

In Develop Model Approach first step we need to select the source task, such that a relationship exist in input and output data, and relational knowledge during mapping to output from input data. And finally constructing a good model for the first objective. Then reuse the model for the second task as starting point of interest. At last, we need to tune model. [13]

In using pre-trained approach we need to select the source model, reuse model, at last tune the model as shown in ”fig 3”.

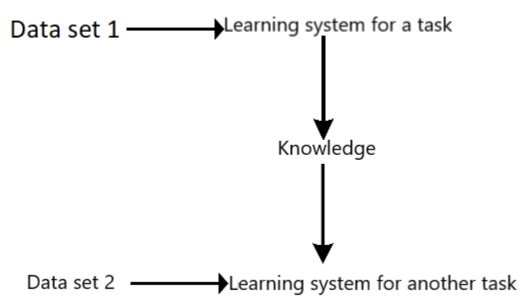

Fig. 3. Transfer Learning

For our work we first selected a pre-trained model as base model, this base model acts as feature extractor, then the output layer is fine tuned and replaced by our predicting layers. These final layers acts as classifiers to predict the existence of covid-19.In our work we are making use of the pre-trained Model Approach by considering VGG16 [16], Mobile Net [17], Resnet50 [18], Inception Net [19] and CNN deep learning models.

After preparing the model we will train the model using data set containing two classes for 20 epochs.To complete the training process fast we stopped training process if there is no improvement in validation loss for continuous 5 epochs and also when there is no improvement in validation loss we are reducing the learning rate by a factor of 0.5. Our Deep Transfer layer model for classification of covid-19 is explained in ”fig 4”

In our Keras implementation of VGG16 model, we used the Kaggle data set. We are using Google Colab to run our model on the GPU for fast training.

In MobileNet convolutions are applied depth wise, meaning convolutions are performed on each color channel separately instead of performing on 3 channels and flattening to 1 [14] .

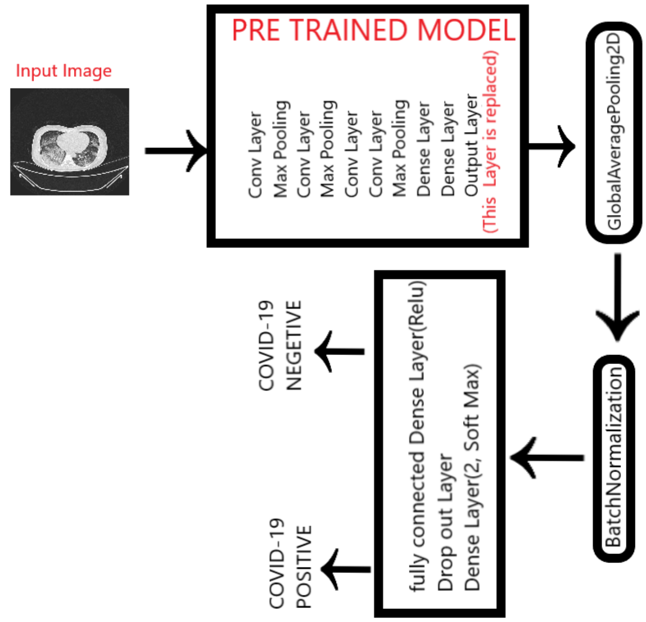

Fig. 4. Transfer Learning based covid-19 classification model

ResNet-50 is a convolutional neural network with 50 layers deep. You can load a pre trained version of the network trained on more than a million images from the Kaggle dataset. [5].

An Inception network is a deep neural network which consists Inception modules which are repeated in its architecture.The InceptionNet was an important milestone in CNN based classifiers development. Before Inception model came into existence, to get the accurate results most of CNN models were developed by researchers by adding more layers in their architecture. The InceptionNet is heavily engineered, it used lot of techniques to get the better performance and accurate results in less time. There are many Inception Networks evolved in recent times,few of them are :

- Inception v1.
- Inception v2
- Inception v3. 1
- Inception v4
- Inception-ResNet.

IV. Results

In this work we considered large data set consisting of 2842 images for training and 200 for validation belonging to two classes to get the accurate results.We started with training the data set with basic CNN Model when trained for 12 epochs before early stopping we got validation accuracy in test set: 81.2% , the graph for training and validation accuracy in ”Fig 5” and the confusion matrix plotted in ”Fig 6”.

Next we trained dataset on different modified pre trained models and evaluated them. ResNet50 had precision of 0.93 and recall 0.71 and for VGG16 precision is 1, recall 0.71. ResNet50 and VGG16 gave validation accuracy of 83.2% and

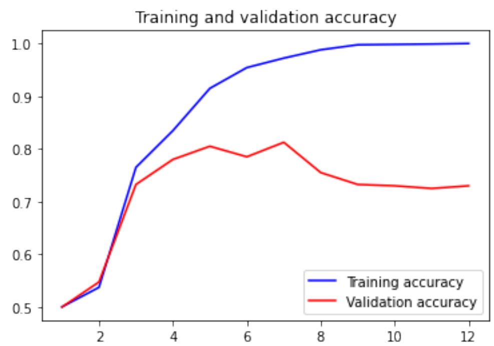

Fig. 5. CNN training and validation accuracy.

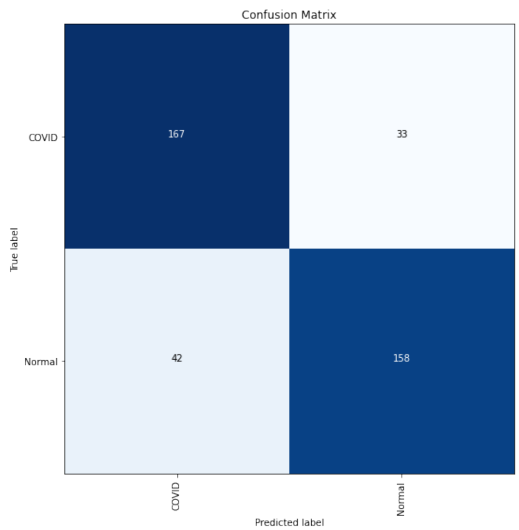

Fig. 6. CNN confusion matrix.

94% respectively which is not desirable in diagnosing medical radiographic images . VGG16 training and validation accuracy and confusion matrix shown in ”fig. 7”,”fig. 8”. ResNet50 training and validation accuracy and confusion matrix shown in ”fig. 9”, ”fig. 10”.

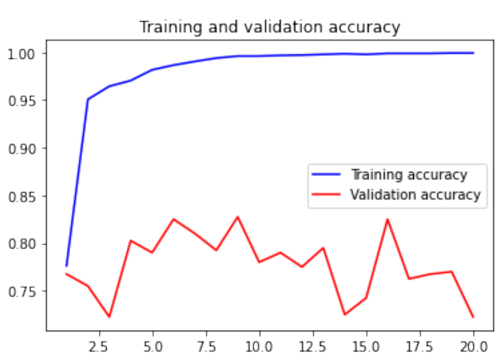

Fig. 7. VGG16 training and validation accuracy.

Then we progressed with MobileNet for transfer learning and modified it, we got Accuracy on test set: 95.2% when

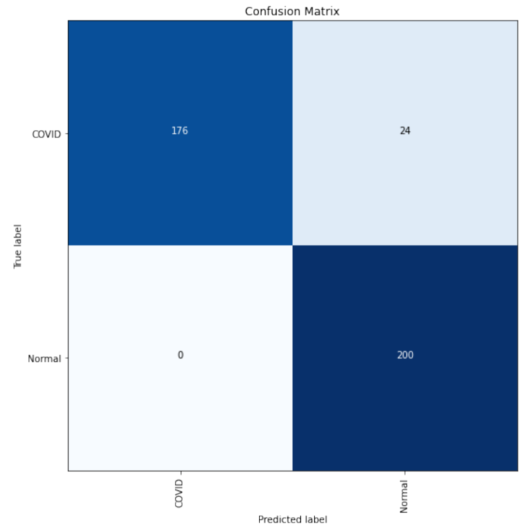

Fig. 8. VGG16 confusion matrix.

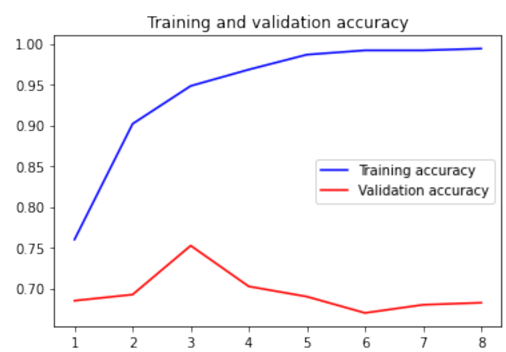

Fig. 9. ResNet50 training and validation accuracy.

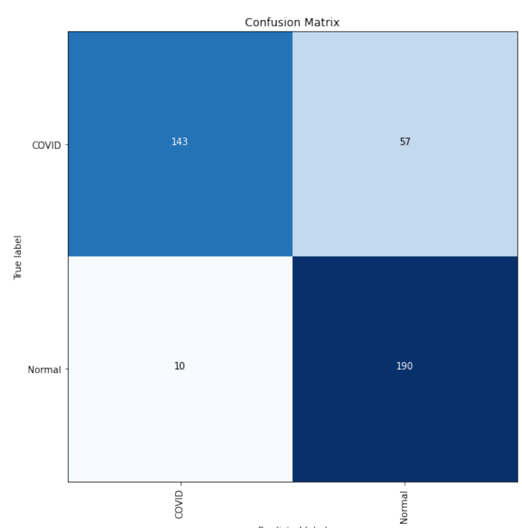

Fig. 10. ResNet50 confusion matrix.

trained for 10 epochs before early stopping. and a good training and validation accuracy as shown in ”fig 11” and we got confusion matrix as shown in ”fig 12”, both precision and recall scores were 0.95, o.95 respectively for modified MobileNet.

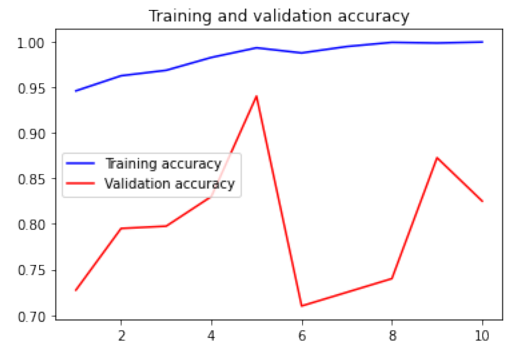

Fig. 11. Mobilenet training and validation accuracy.

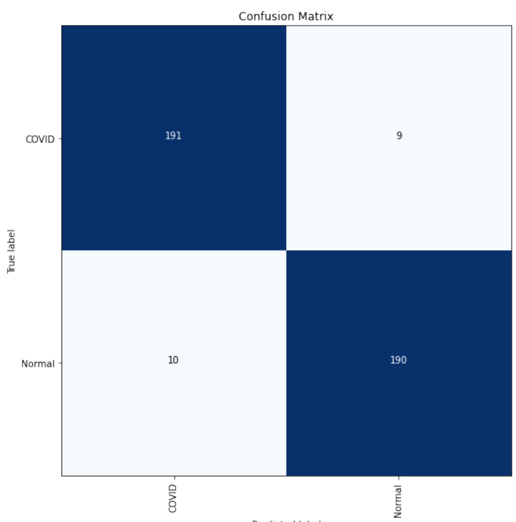

Fig. 12. MobileNet confusion matrix.

Finally in our work we used InceptionResNet v2 pre trained model and fine tuned it. From this modified model we obtained accuracy on test set: 99% , training and validation accuracy as shown in ”fig. 13” . The plotted confusion matrix ”fig. 14”. shows that the precision is 0.98 and Recall score is 1 which means there are almost no true negatives in prediction which is very desirable in medical image diagnosis.

The accuracy and loss values over training and validation sets of every model at best epoch are listed in the below ”table 1”.

We evaluated performance matrix on above discussed models based on F1 score, precision and recall scores, among all InceptionNet performed well over remaining models with F1 score of 99%.

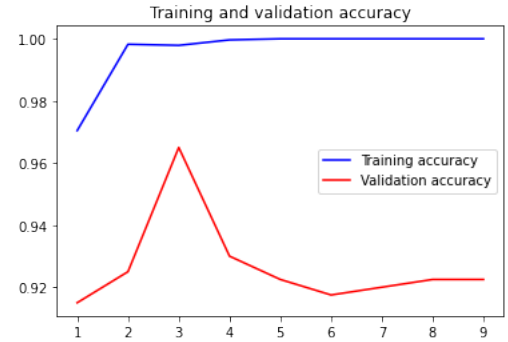

Fig. 13. InceptionNet training and validation accuracy.

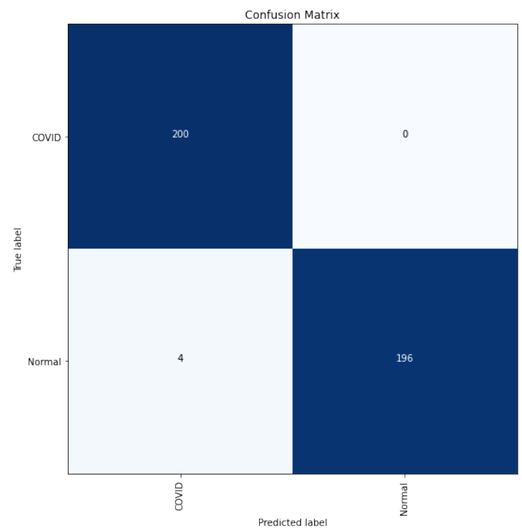

Fig. 14. InceptionNet confusion matrix.

TABLE I
ACCURACY AND LOSS VALUES ON TRAINING AND VALIDATION AT BEST EPOCH

Model	accuracy	loss	Val accuracy	Val loss
InceptionNet	0.9996	0.0025	0.9300	0.1533
MobileNet	0.9930	0.0471	0.9400	0.1952
VGG16	0.9961	0.0549	0.8275	0.4229
ResNet50	0.9683	0.1413	0.7025	0.4724
CNN	0.9722	0.0843	0.8125	0.3777

TABLE II
RESULTS PRODUCED BY VARIOUS MODELS ON COVID-19

Model	F1 Score	Precision	Recall
InceptionNet	0.99	0.98	1
MobileNet	0.95	0.95	0.95
VGG16	0.93	1	0.88
ResNet50	0.80	0.93	0.71
CNN	0.80	0.79	0.83

V. Conclusion

This work progressed on developing an accurate binary classifier which uses transfer learning technique by considering existing pre trained model as backbone for predicting the presence of COVID-19 in HRCT images are not. Our work showed that modified InceptionResNetV2 model giving an accuracy of 99% and is almost predicting every HRCT image correctly. This work suggesting that with more research we can use HRCT images for diagnosing COVID-19 as an alternate solution for testing the disease. This work also investigates the performances of pre trained deep learning models on HRCT images and evaluates them based on their F1 scores.

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