

COVID-19 SEVERITY PREDICTION USING DEEP LEARNING MODELS – COMPARATIVE STUDY

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Abstract: In response to the exponential rise in COVID-19 instances, healthcare professionals have been seeking for strict automated detection measures to stop COVID from spreading while simultaneously attempting to restrict device processing needs. Additionally, we must comprehend the severity of the COVID infection based on the harm the infection has done to the lungs to properly treat impacted individuals. We choose a suitable CNN model as a result after performing an initial comparison analysis of many well-known CNN models. Using a dataset generated from sources like prior papers and other internet resources, this study provides an ensemble model that is exact and effective and is built on deep learning Convolutional Neural Networks (CNN). The dataset is altered in several ways to boost its accuracy. To choose the optimal deep-learning model for our application, we are performing a comparative study. We assessed the benefits and drawbacks of many commercial CNN models, including VGG16, VGG19, and Densenet 121. To select the optimal model for provided dataset, the accuracy comparative study is constructed. VGG16 model had highest accuracy, coming in at 82.46 %. The study was conducted to determine the optimum way for our multi-modal picture classification, which, with a little modification, functions well, rather than to accurately assess how well each method did.

Keywords: DenseNet-121, VGG-16, VGG-19, COVID-Severity, Comparison

I. INTRODUCTION

Colds, the flu, and more severe disorders like SARS-CoV-2 and MERS-CoV are all known to be brought on by viruses in the Coronaviridae family (SARS). COVID-19 has the potential to result in lung issues such as pneumonia and, in severe situations, ARDS. The coronavirus pandemic has had a detrimental effect on medical services. Especially in intensive care units (ICUs), patients who are unwell have placed wholly unexpected demands on emergency treatment [1]. Another serious COVID-19 adverse effect, sepsis, can harm the lungs and other organs permanently. Recent coronavirus strains have the potential to induce more serious respiratory

illnesses, including bronchitis, which may require hospitalization. The development of shortness of breath finally results in acute respiratory distress syndrome (ARDS), a form of lung failure. Patients with ARDS typically have trouble breathing on their own and may need support from a ventilator to improve the body's circulation of oxygen [2]. Since the COVID-19 outbreak started, scientists have been searching for a quicker replacement for the reverse transcription-polymerase chain reaction (RT-PCR) test, which is used for COVID-19 identification. The outcomes of the test could contain both false positives and false negatives. Scientists are looking for a better diagnostic technique. The global issue was that the number of infected people were growing exponentially and the resources required to deal with them were limited. As a result there were shortage of resources like beds, oxygen cylinders etc. The COVID19 Severity Detection System will enable us to identify the hotspots where most sever patients are accumulated, thus enabling the government officials to distribute additional resources in that order. It will also help us prioritize more severe patients and decrease the death rate caused by it.

To perform this study and develop the severity detain system, we implemented a trained model (DenseNet Architecture) on the features extracted from the 2-dimensional images of the lung which were transformed from the 3-dimensional CT scans obtained, to produce the output of this paper. Finally, we compared DenseNet121 architecture with two alternative CNN designs (VGG16, VGG19). In order to get better outcomes and greater accuracy.

II. LITERATURE OVERVIEW

Using the CNN technology, this study [4] presents a novel COVID-19 illness severity categorization method according to the severity of infection: mild, moderate, severe, and critical. A CNN model is presented with an average accuracy of 95.52%. The authors of this study [5] looked at COVID-19 diagnoses made with a chest CT with an eye toward AI. Based on the categorization tasks, they divided the studies into four categories: COVID19/normal, COVID19/non-COVID19 pneumonia, and severity. The accuracy is 99.5%. In their work, the researchers created COVID-Net CT-S, group of deep CNNs, determining the degree of lung sick-



ness brought on by COVID-19 infection [6]. In order to understand volumetric visual indicators characterising infection intensity, a 3D residual architectural design is applied. The study discovered that a customised training technique can enhance network performance and generalisation on a patient cohort with uneven severity levels and high equipment and procedure instability. The study [7] provided a system for computer-aided diagnostics in which they developed a back propagation neural network and transfer learning-based severity detection approach. To improve learning capacity, the authors used data augmentation. It had a 98.5% accuracy rate. According to the results, combining ResNet-50 and DenseNet-201 architecture features resulted in more precise findings when applied to test data. When compared to cutting-edge techniques, this COVID-19 severity detection system provided 97.84% average classification accuracy. This study [8], establishes a new deep CNN for segmenting chest CT images with COVID19 infections. The first section of the paper contains a large and recent lung computed tomography image collection consisting of 21,658, annotated images from 861 people suffering from COVID19. A feature variation block is introduced in the proposed deep CNN that adaptively adjusts the global properties of the features for segmenting COVID19 infection. The proposed network enhances the ability of COVID19 infections to be segmented, connects to other methods, and advances the development of infection treatment. Since there is so little publicly available COVID-19 imaging data, conventional techniques tend to overfit. As a solution to this problem, the authors of this study [9] created a novel automated segmentation process for COVID-19-infected areas that can manage minimal datasets by utilizing variant databases. The researchers developed a very precise and powerful classification model using a 5-fold cross-validation on 20 CT images of COVID-19 patients without overfitting the limited data. Dice similarity coefficients of 0.956 for the lungs and 0.761 for infection were obtained using this approach. This paper [10], highlighted an entirely automated approach for lung field segmentation in CXR. To provide an initial segmentation, one CNN model based on AlexNet is used to conduct patch classification. A second CNN model based on ResNet18 is then used to reconstruct the missing lung field parts. Finally, the output of the proposed method is generated by combining the results of initial segmentation and reconstruction. The proposed method is validated using the Montgomery County Chest X-ray dataset.

III. DATASET DESCRIPTION

Due to the global threat of COVID-19 infection, it is essential to have access to CT images and clinical data to advise clinical decisions, deepen our understanding of the virus's infection patterns, and provide systematic models for early diagnosis and prompt medical interventions. To prevent the spread of COVID-19 infection, the strategy is to create a

comprehensive database with public access to CT images and related clinical symptoms. The name of the dataset used for this study is the "MOSMEDDATA: CHEST CT SCANS WITH COVID-19 RELATED FINDINGS DATASET". It includes both anonymous human lung computed tomography (CT) scans with and without COVID-19-related abnormalities. CT scans of patients were facilitated from municipal hospitals in Moscow, Russia [11]. The dataset contains 1110 studies and were collected between March 1 and April 25, 2020. This dataset includes anonymous human lung computed tomography (CT) scans with and without COVID-19-related abnormalities (CT1-CT4) (CT0). It has 42% males, 56% females, 2% other; range in age from 18 to 97; median age is 47. All studies (n=1110) were divided into 5 groups in the first stage. According to categorization, there were 254 cases in CT-0, 684 cases in CT-1, 125 cases in CT-2, 45 cases in CT-3, and 2 cases in CT-4, where CT-0 to CT-4 represent the severity from mild zero to severe. Second, each study has been archived into a Gzip file and saved in NifTI format. The classification of CT-Scans into 5 categories, which makes it more advantageous for training and verifying the machine learning models utilized, was the primary driving force behind utilizing this dataset. Permanent Link- https://mosmed.ai/datasets/covid19_1110

IV. METHODOLOGY

In our proposed methodology, we used 3 neural network models-DenseNet121, VGG-16, and VGG-19. A comparative study of the model performance and finding the optimal model for predicting COVID19 severity based on CT images was the prime objective of this paper. Moreover, in our implementation, we have used 3-D as well as 2-D CT images to train our model to compare the accuracy and performance based on reduced image features. The effect of reduced parameters of 2-D CT images as compared to 3-D on the accuracy and performance of the model is discussed.

4.1. Image Pre-processing: Dimensionality reduction

In our approach, the dataset used had the images in .nii.gz format. This format contains more image features because it is 3-D. To compare the results we had to convert the 3D images into 2D slices. This slicing was achieved with the help of an application called ITK-SNAP. The goal of this software was to develop a tool that would be easy to use and would be dedicated to a single task, segmentation. The three orthogonal cut planes are capable of labelling, and the results can be rendered in three dimensions. This makes it simpler to guarantee that the segmentation keeps a reasonable shape in three dimensions. The ITK-SNAP application's slicing feature is used to convert Computed Tomography (CT) images in the NII format to .PNG format. 2-D images obtained on conversion are used for model training. Each image was manually loaded and the specific 2-D slice was extracted. Converting 3-D images significantly reduced the

total features to be trained by our machine learning models and significantly reduced processing time.

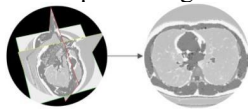


Fig. 1.3D to 2D Image Conversion

4.2. Approach

A computational model called deep learning, a subclass of machine learning, aims to understand how the brain reacts to external inputs. Several convolutional filters are used to extract the various level features from the input. The number of filters, kernel size, and collection of characteristics that each filter learns differ for each layer [4]. One can employ pre-trained models without their final fully connected layer to produce noticeably different maps. DenseNet121 was compared to VGG1-16 and VGG-19 in this paper. By comparing these models, conclusions about the use of dif-

ferent models in different situations can be drawn. These characteristics are used to divide CT imaging into five categories based on the severity of the chest. The data is divided into three groups: training (70%), validation (15%), and testing (15%).

4.3. COVID-19 Severity Detection

Hospitals can use COVID-19 severity detection as a crucial evaluation method to categorize patients according to the degree of their lung injury. The features of CT image are employed in this study to determine the patient's severity of the condition. This work investigated three neural network models - DenseNet121, VGG-16, and VGG-19 to determine their performance in accurately predicting COVID-19 severity. The patient's severity condition was classified into 4 categories – zero, mild, moderate, severe, and critical. Based on the severity score predicted by the model patients having severe and critical symptoms can be given special treatment.

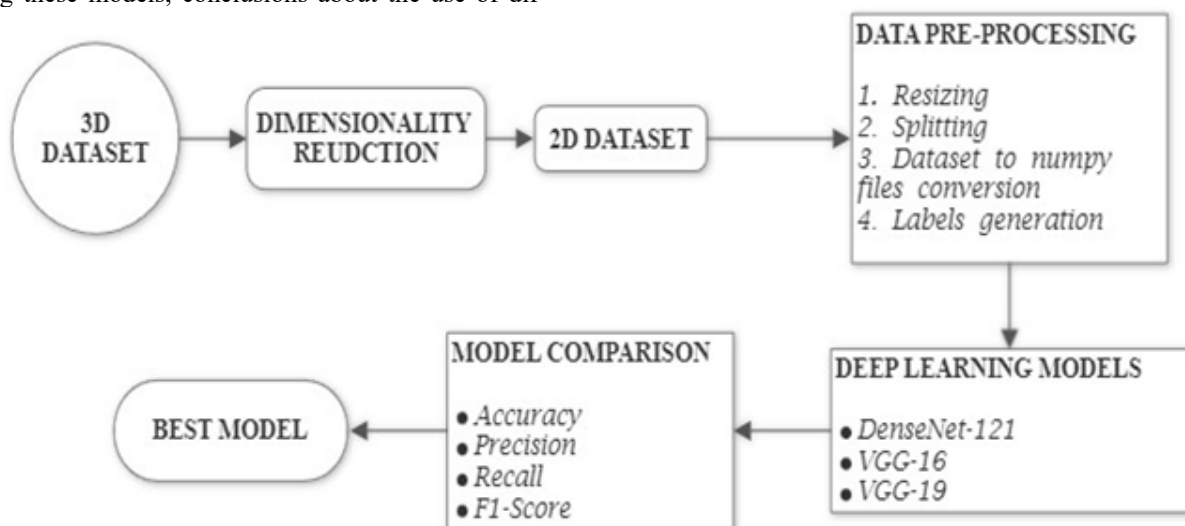


Fig. 2. Architectural Diagram Followed

V. RESULTS AND ANALYSIS

Deep learning models are used to do a comparative study for COVID-19 severity identification, and the findings are presented individually. A dataset of 1110CT scan pictures was split into 5 groups (CT-0 0-20%, CT-1 21-40%, CT-2 41-60%, CT-3 61-80%, and CT-4 81-100%) according to the severity of COVID infection. The following criteria are used to define and rate the performance of a model:

Precision: It is the percentage of recovered occurrences that are relevant. Computed by dividing total number of both true positives and false positives by true positives.

$$\text{Precision} = \frac{TP}{(TP + FP)} \quad (4)$$

Recall: It is true positives divided by total of true positives and false negatives

$$\text{Recall} = \frac{TP}{(TP + FN)} \quad (5)$$

F1-score: The harmonic mean of recall and accuracy is a common definition for the F1-score. Only when recall and accuracy are both 1 does the F1-score equal 1.

$$\text{F1score} = \frac{2 * P * R}{(P + R)} \quad (6)$$

5.1. DenseNet-121

50 epochs were used for the dataset, and the accuracy was 79.82%. From the confusion matrix we can see that the DenseNet-121 model classified 23 test cases, 66 test cases, 2 test cases, 0 test cases and 0 test cases correctly out of 26 test cases, 69 test cases, 13 test cases, 5 test cases and 1 test case for CT-0, CT-1, CT-2, CT-3 and CT-4 categories respectively.

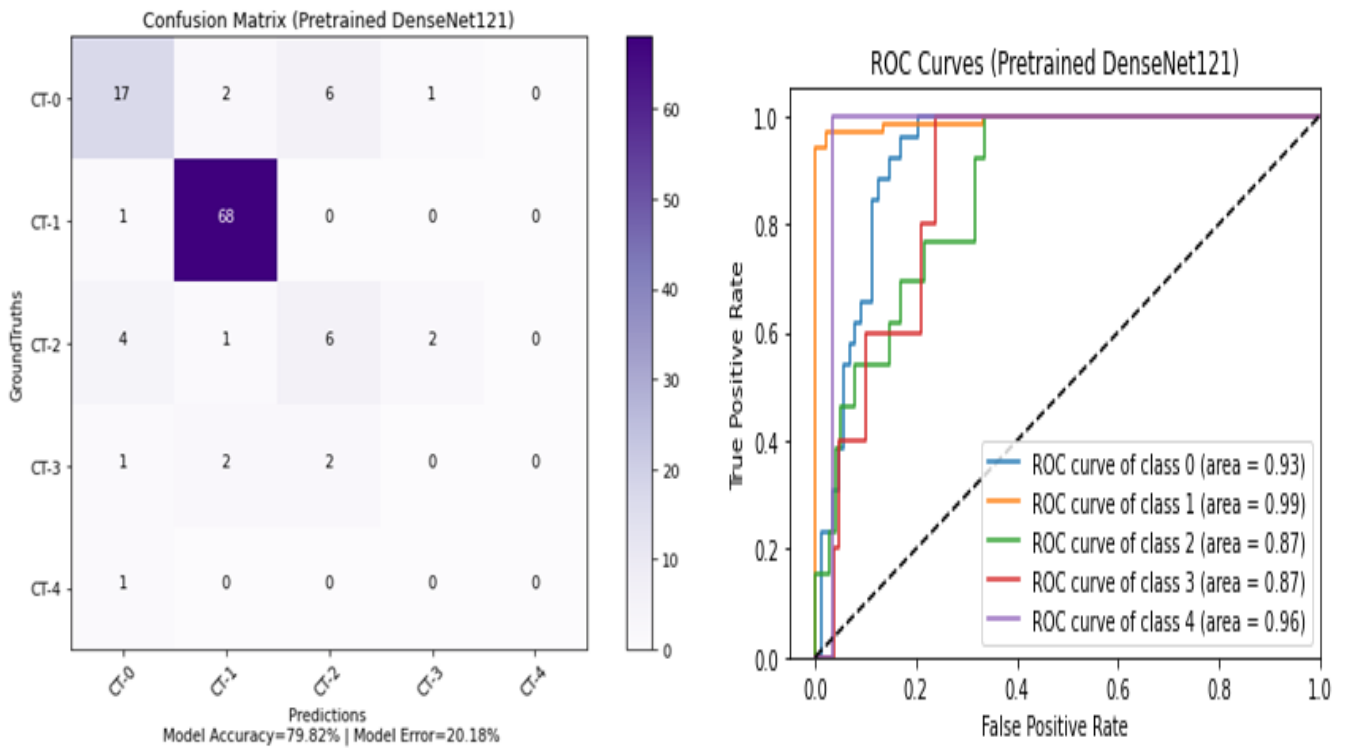


Fig. 3. (Left to Right) DenseNet-121 Confusion Matrix, DenseNet-121 ROC Curve

5.2. VGG-16

50 epochs are used for the dataset, with an accuracy of 82.46%. From the confusion matrix we can see that the VGG-16 model classified 25 test cases, 69 test cases, 0 test cases, 0 test cases and 0 test cases correctly out of 26 test cases, 69 test cases, 13 test cases, 5 test cases and 1 test case for CT-0, CT-1, CT-2, CT-3 and CT-4 categories respectively.

cases, 0 test cases and 0 test cases correctly out of 26 test cases, 69 test cases, 13 test cases, 5 test cases and 1 test case for CT-0, CT-1, CT-2, CT-3 and CT-4 categories respectively.

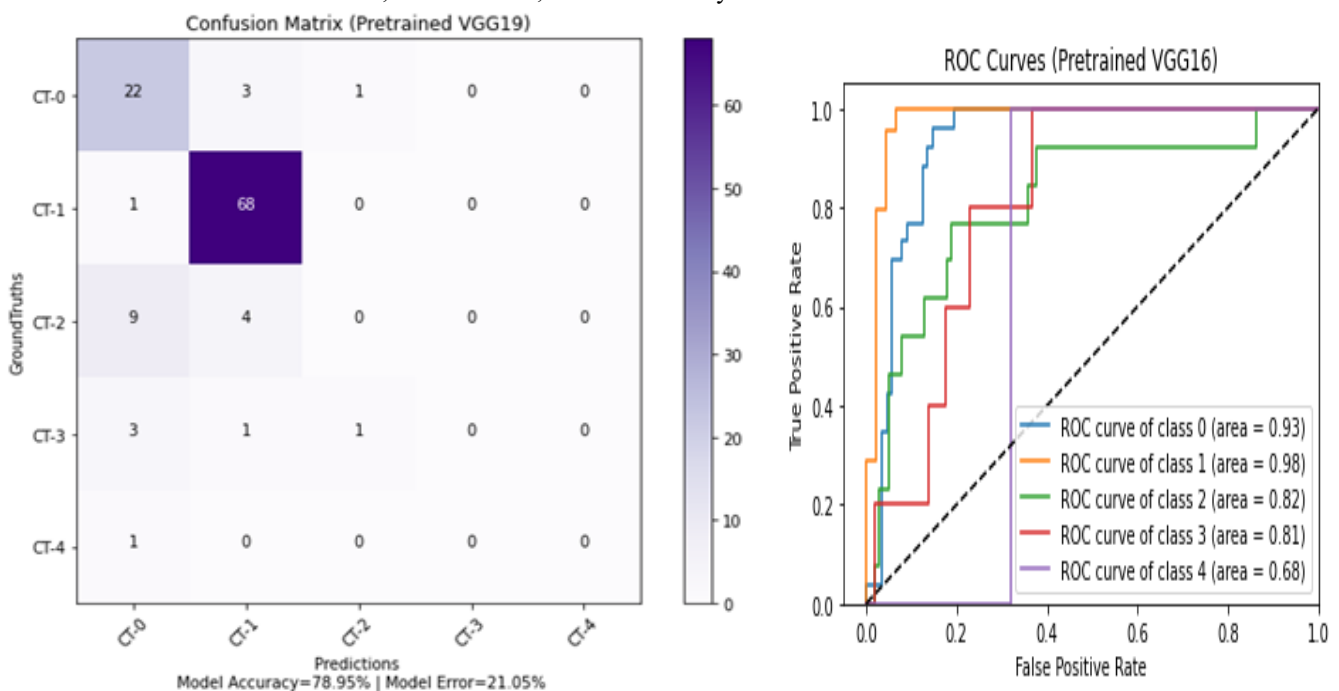


Fig. 4. (Left to Right) VGG-16 Confusion Matrix, VGG-16 ROC Curve

5.3. VGG-19

50 epochs were used for the dataset, and the accuracy was 79.82%. From the confusion matrix, we can see that the VGG-19 model classified 23 test cases, 68 test cases, 0 test cases, 0 test cases, and 0 test cases correctly out of 26 test cases, 69 test cases, 13 test cases, 5 test cases, and 1 test case for CT-0, CT-1, CT-2, CT-3, and CT-4 categories respectively.

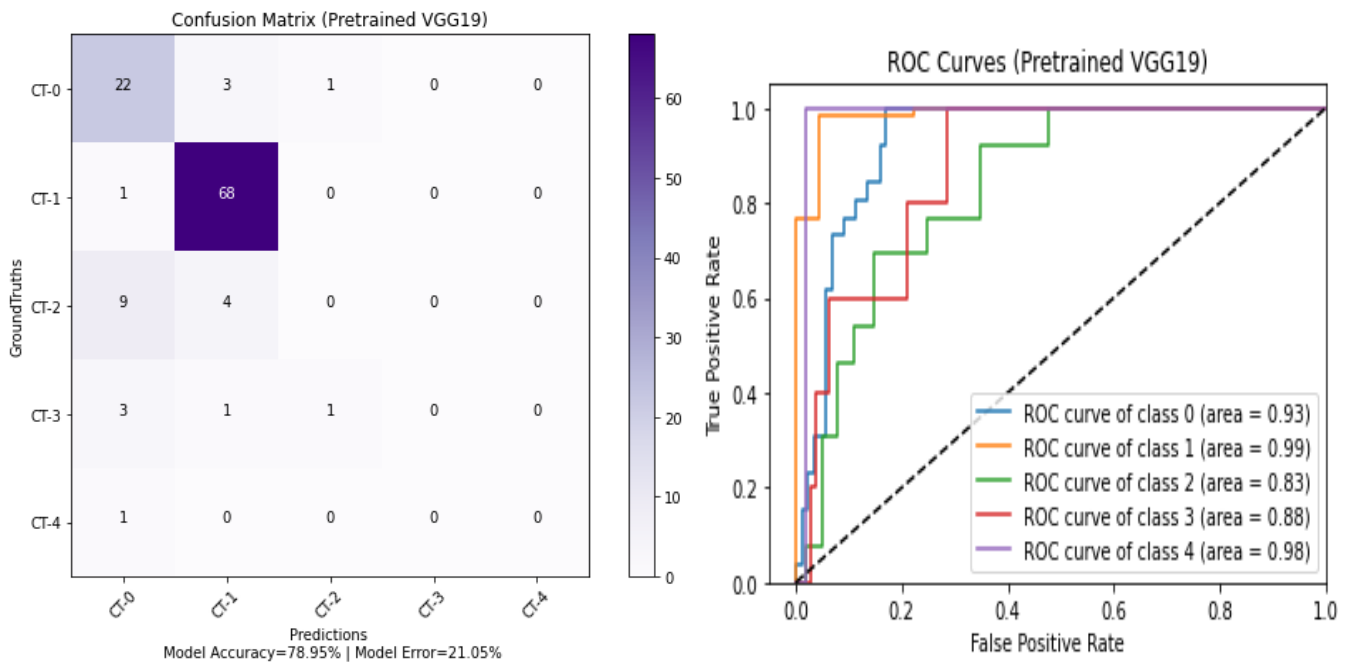


Fig. 5. (Left to Right) VGG-19 Confusion Matrix, VGG-19 ROC Curve

The execution for recognition of the severity of COVID-19 using various deep models is shown in Table 1. Comparing table VGG16 is accurate on the CT-Scan dataset.

Table 1. Comparative Analysis of DenseNet-121, VGG-16 & VGG-19

Deep Learning Model	Accuracy (%)	Precision(%)	Recall (%)	F1-Score (%)
DenseNet-121	79.82	77.42	79.82	78.54
VGG-16	82.46	71.91	82.46	76.26
VGG-19	78.95	68.09	78.95	72.96

VI. CONCLUSION AND FUTURE WORK

Corona virus has a direct effect on lung cells that may harm extremely, and if no longer identified early. It will result in irreversible harm, which includes death. The virus is diagnosed using X-ray or CT pictures collectively with pcr15 effects. In this paper, we brought 3 powerful deep-learning models for COVID-19 severity detection using CT images for comparison. On evaluation, it is observed that VGG16 has given us the best results with an accuracy of 82.46% which is followed by the VGG19 model and then by the

DenseNet-121 model with accuracies of 81.58% and 79.82% respectively.

The method by which the model is built could also be altered; 3D CT pictures are preferred over 2D CT images in order to provide information on the variability among the various images and include it in the trainable features. Building a model from the provided dataset for the kind of images we used as real-world examples is a tedious process, and no more research in this area could be done because of the computing constraints encountered during model training. The usage of 3D CT images is preferred since it will



improve the model's overall performance and training efficiency. A larger dataset and 3D CT images would both be improvements to our suggested approach.

VII. REFERENCES

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