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RESPIRONET: Leveraging UNET Architecture for Effective COVID-19 Severity Prediction from Pulmonary CT Images

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***Abstract*—Covid-19, the most deadly word in recent years which worst hit the entire world, is still prevailing as a variant of concern. As the transmissibility of the virus is high, a quick and efficient approach to detect the presence of COVID and to give medical attention to those patients is of paramount importance. The research work proposes an effective deep neural network approach to quantify the severity score of COVID-19 infection from CT Lung images. Leveraging the Computer Vision techniques, semantic segmentation (SegNet) was applied to CT images to extract the lungs. Subsequently, a deep convolutional Encoder-Decoder Architecture was developed to assess the severity score of lung infection. Furthermore, to be well-balanced in accuracy and computational speed, various hyper parameters were investigated to build the effectual model. Evidently, as the severity classification (Mild, Moderate, and Severe, Critical) is preceded by lung extraction, the proposed framework for GGO segmentation demonstrates the ability to generate results with state-of-the-art segmentation accuracy of 96% and prediction accuracy of 98.9%.**

Keywords— COVID-19, Semantic Segmentation, CT images, UNET, transfer learning, Hyper parameters, Severity score.

Graphical Abstract

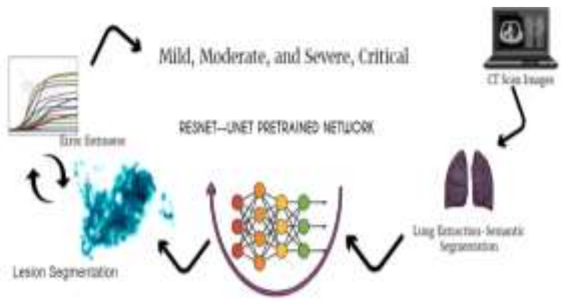

Fig.1. RESPIRONET: COVID -19 Severity Prediction Model

I. INTRODUCTION

The European Center for Disease Prevention and Control reported a total of approximately 289 million covid cases and around 5.4 million reported deaths worldwide since the start of 2022. [27].The deadly virus transcended at an unprecedented speed, overwhelming the health care support system. This necessitates an efficient triage system to quantify the severity score of COVID-19. Initially, the virus presence is confirmed with a positive reverse transcription-polymerase chain reaction test with oral and nasopharyngeal swab samples. The insufficient viral load in the swab samples decreased the sensitivity of the test down to 60 to70 %. This inefficiency during the earlier stages of the infection can be addressed through Radiology tests. Radiological studies have investigated different modalities like ultrasound, chest x-ray, or positron emission tomography/computed tomography (PET/CT) scan. The Radiological Society of North America, in their research journal 'Radiology', highlighted the importance of CT imaging for disease detection. They confirmed that the images are key components for the disease diagnosis. The clinical features of 41 patients initially admitted in Wuhan had abnormalities on their CT scan images

CT scan images have manifested to be more effective for the diagnosis, to determine the severity, and to guide the treatment procedure. The severity of Covid19 can be mild, moderate, or severe. The radiographic evidence is absent for mild cases but is significant for moderate and severe infections. Recent studies on biomedical computer vision have witnessed a considerable rise in the use of Convolutional Neural Network (CNN) and it has substantiated to be the best performer for skin lesion classification, breast cancer detection, brain tumor detection and Tuberculosis detection. In this context, our research study presents an efficient model by exploiting the variants of the CNN to identify and quantify the CT Lung images to isolate critical patients.

Abbreviations

COVID 19 Coronavirus Disease 2019
CT scan Computed Tomography Scan
CNN Convolutional Neural Network
GGO ground-glass opacity
RESPIRONET
SSP Severity Score Prediction
SSR Severity Range Prediction

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II. Related Work

COVID-19 disease was declared a global pandemic, which negatively impacted human life in many aspects. Research work on COVID-19 is being successfully carried out in many directions. TB screening, lung cancer diagnosis and, lung nodule detection, are other kinds of lung-based diseases, but covid-19 is something different as well as so easy to spread over the humans. Doctors identify the morphological patterns of the lesions in the lungs to predict COVID using the Chest scans such as X-rays and Computer tomography (CT) scans [8]. Classification, object identification, and picture segmentation are few computer vision applications where ML and DL approaches have demonstrated ground-breaking performance. [1]. Enormous studies are conducted on how to spot COVID-19 disease using CT scan images and chest X-ray images. Many research works on CT scan-based diagnosis are conducted and published in international journals.[2]. Rahman et al. proposed a system to contain the spread of COVID-19 by performing face mask detection in a smart city [3]. Harmon et al. [4] trained and validated a series of deep learning networks. Wang et al. [6] employed a deep regression framework for automatic pneumonia identification by integrating clinical information like age, gender, past medical history, etc., with the CT scan images. Visual features are extracted from CT scan images using RNN (Recurrent Neural Network) and ResNet50. Generally, clinical details like fever, cough, and difficulty in breathing are collected from the patients. They are analyzed together with the demographic features like age and gender using LSTM (Long Short Term Memory). In the end, a regression framework was enrolled to classify the suspected patient as Community-acquired pneumonia (CAP) or not [1]. Qiblawey et al. proposed a framework and evaluated over 900 clinical cases and achieved remarkable accuracy level. In line with that Mei et al. [5] proposed a mixed AI algorithm that combines clinical data with the results of a chest CT. To differentiate COVID-19 patients from non-COVID patients, clinical indicators such as fever, coughing, irregular breathing, and laboratory testing are used. The joint model achieved high discriminative performance with 0.92 area under the curve (AUC) outperforming senior radiologists. The potential pitfall of the combined system is the availability of clinical information when a huge number of patients are waiting to be diagnosed, moreover, this method is not able to show the infected area of the lung [1]. Pedro Silva et al.[7] proposed a model for the detection of COVID-19 patterns in CT images namely Efficient vidNet. Soares et al. [8] made a public repository of CT scans dataset, consisting of 2482 CT scans taken from hospitals in the city of Sao Paulo, Brazil. They have reported an accuracy, sensitivity, and positive predictive value of 97.38%, 95.53%, and 99.16%, respectively.

Following the monumental victory of deep learning techniques and its applications in medical image analysis, researchers have used radiology reports such as CT-scans and x-rays to detect COVID-19 [9]. CNN was utilized by Chowdhury et al. [10] to create their diagnosis model from chest x-rays. More number of research work was carried out based on pre-trained networks that were used to diagnose COVID-19. [11–13] used ResNet and obtained accuracies of 96%. Li et al [12] used DenseNet121 on X-ray images and achieved an 88% accuracy with AUC score of 0.97. A lesion identification approach was proposed by Zhou et al. [13] for estimating COVID-19 infection areas from the chest CT scans. Rahaman et al [14] examined 15 various pre-trained CNN models and found that VGG-19 had the highest classification accuracy at 89.3%. InceptionResnetV2, DenseNet201, Resnet50, MobilenetV2, InceptionV3, VGG16, and VGG19 were employed by Asnaoui and Chawki [15]. The highest accuracy of 92.18% was obtained using InceptionResnetV2. Wu et al [16] implemented multiple CNN models to categorize COVID-positive individuals from CT scan images. A 3D deep CNN (DeCovNET) was proposed by Wang et al [17] to detect COVID-19. He et al [18] introduced a small dataset of lung images in CT scans and put forward an approach named Self-Trans i.e. self-supervised learning with transfer learning.

III. Motivation

Although the literature shows promising results, there is still scope for improvement in predicting the severity of COVID. This work aims to build a severity prediction model that employs pixel-wise labeling a.k.a semantic segmentation to extract the lungs from the CT images. The lung extracted is further semantically segmented to get the Ground Glass Opacity (GGO), a hazy, white-flecked pattern visible on lung CT scans that indicates increased density. The segmented lesion is used to assess the severity of infected lungs. This gives a deeper understanding of the radiology images in the lowest granule level.

The remainder of the paper is organized thus: Section 2 details the dataset used to conduct the study. The proposed methodology adopted is delineated in Section 3. Section 4 exhibits the experimental setup and results obtained. Section 5 tabulates the extensive set of investigations done on various hyper parameters to optimize the model, along with the discussions and analysis. Finally, the concluding remarks with limitations are drawn in Section 6.

Database Used

SARS-CoV-2 CT scan dataset [*Soares, E.; Angelov, P.; Biaso, S.; Froes, M.H.; Abe, D.K. SARS-CoV-2 CT-scan dataset: A large dataset of real patients CT scans for SARS-CoV-2 identification. medRxiv 2020. [CrossRef]*] was used in this research for Covid-19 severity prediction. The dataset comprises 1252 CT image positive samples and 1230 negative samples for SARS- CoV-2 prediction. As the CT image features could confidently prove the existence of Covid, this repository is made public to encourage research contributions to address Covid detection and treatment. The images are collected from the patients of hospitals from Sau Paulo, Brazil.

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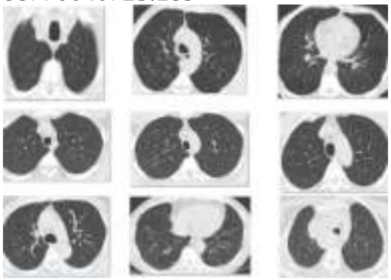

Fig. 1. CT scans images of SARS-CoV-2 infection -ve samples in axial projection

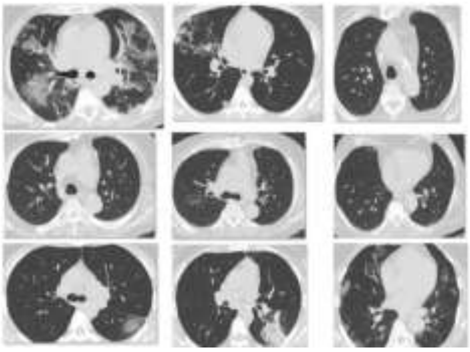

Fig.2. CT scan images of SARS-CoV-2 infection +ve samples in axial projection

IV. PROPOSED METHODOLOGY

We present a simple yet mighty COVID Prediction Framework–RESPIRONET illustrated in Fig.3. The proposed system comprises three phases. The first stage of the work builds a custom SegNet model using the semantically labeled CT images. A great deal of attention was made to label the pixels using the Image Labeller App to generate the ground truth. This sets the way to take out the Region of Interest (Lungs) from the CT images using the lung mask generated. The extracted lungs are further semantically labeled pixel-wise. Stage 2 employs a U-Net Architecture to segment the Ground Glass Opacities (GGO, from now on). Transfer learning from a pre-trained network was adapted on the encoder layers of UNET with Resnet18 weights to build the segmentation networks. The lesion mask generated from stage 2 helps to classify COVID from Non-COVID images. Stage 3 uses the segmented lesions to predict the severity score of the infection as MILD or SEVERE or MODERATE or CRITICAL

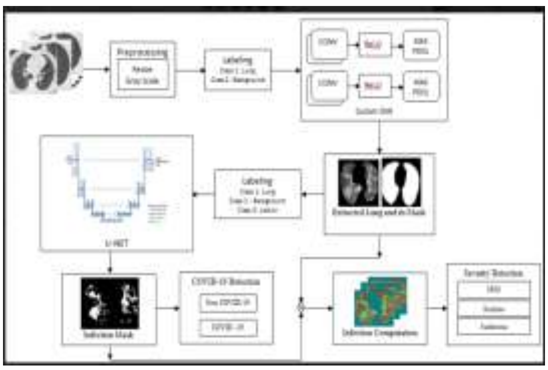

Fig.3. RESPIRONET Framework for COVID Severity Prediction

Preliminary Steps - Image Preprocessing

Data quality being a priority concern for deep learning models, grayscale conversion and image resizing for CNN were applied to the dataset. The CT lung images were converted to grayscale images that contain only brightness information, thereby reducing the processing time. All input images were resized to 256*256 to feed CNN with a unified dimension. In addition, to perform Image Enhancement, Contrast limited adaptive histogram equalization (CLAHE) image enhancement was tried out to improve the local contrast of the images.

Lung Extraction using Custom SegNet

To emerge with an answer to the question "What is in the image? And where it is located? "in Biomedical images, Semantic segmentation was exploited. Semantic Segmentation is the process of assigning each pixel in a picture a class that corresponds to the thing it is representing. This dense prediction returns the feature map that contains the class label represented as an integer. The SegNet CNN architecture for lung segmentation consists of an encoder path and decoder path terminated by a pixel classification layer. The Encoder path performs convolutions using the filters and generates the feature maps. The Decoder path performs upsampling of the feature maps from the encoder. The final high dimensional feature map is fed to the softmax classification layer. Each pixel is labeled with the class corresponding to the highest probability. The proposed custom SegNet CNN model was crafted with Filter size=7, the number of conv layers=3, followed by Batch Normalization, RELU, and max pooling in each block. The best hyper parameters were chosen by running a Bayesian Optimizer on a set of hyper parameter values. Fig 4 apparently shows that the segmentation network works best when the Kernel filter size for the Convolution layer is set to 7. The outcome of the custom SegNet Model for Lung Segmentation is presented in Fig: 6. The lungs and background are segmented and shown in discriminating colors.

Bayesian Hyper parameter Optimization

To build this effective custom segmentation model for lung extraction, Bayesian Hyper parameter Optimization was experimented with. Bayesian Optimization works by building a probability model mapping the hyper parameter values to the objective function. The objective function is used to find the most suited hyper parameters to evaluate the true objective function.

$$x^* = \text{argmin } f(x) \quad (1)$$

Where x* is the set of hyper parameter values that gives the lowest objective scores like RMSE. The most promising set of hyper parameter values is estimated in a very short time. The best-suited hyper parameters were used to construct the segmentation model. Fig 5 lists the best suited hyper parameter values like MaxEpochs=100; MiniBatchSize=64; Learning Rate=1e-3; Optimizer = sgdm; No. of Layers = 3, Filter Size = 7.

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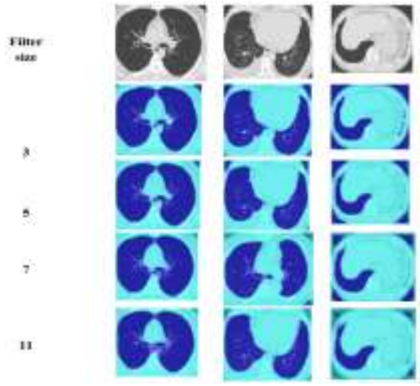

Fig.4. Visual Comparison of segmentation by varying the Filter Size

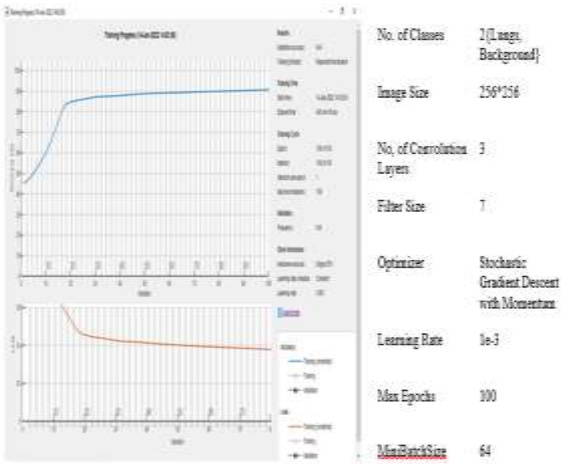

Fig.5. SegNet for Lung Extraction- Training Progress and Bayesian Hyper parameter Optimization

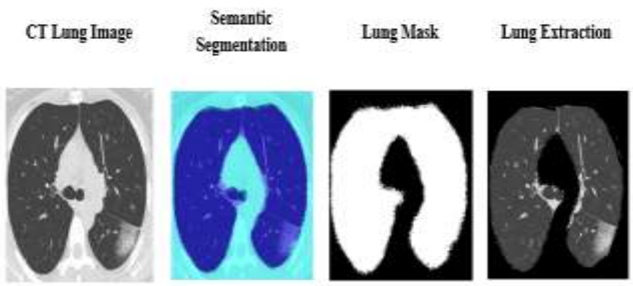

Fig. 6. Phase 1: Lung Extraction Using Custom SegNet Model with the Optimized Hyperparameters

Covid Lesion Segmentation using UNET

The second stage of the proposed work aims to segment the GGO areas in the CT scan images. U-Net is a segmentation network that has performed exceedingly well in biomedical image segmentation. The specialty of the network is that it can outperform other segmentation networks by using only very few images. These highlighted features of the UNET architecture makes it a viable alternative for other CNN architectures. U-net is an encoder-decoder architecture that classifies each pixel of the image and also projects the discriminative features learned at the pixel space. The first half of the UNET architecture called the Contracting path is the Encoder (Fig.7). Usually, it is a pre-trained classification network like VGG or ResNet that constitutes of convolution blocks followed by a max pool layer to encode the input image into feature representations at multiple different levels. In this proposed work, we have used RESNET-18 in the contracting path of the U-Net architecture and performed transfer learning. It saves huge efforts required to re-invent the wheel and transfers the weights learned to the problem at hand. The reason for using ResNet is that it is considerably more deeply nested, but because global average pooling is used, the model size is actually much lower. It also tackles the vanishing gradient problem. The second half of the architecture also called as Expanding path is the decoder. The goal is to semantically project the discriminative features learned by the encoder onto the high resolution pixel space to get a dense classification. The decoder consists of upsampling and Skip Connections followed by regular convolution operations.

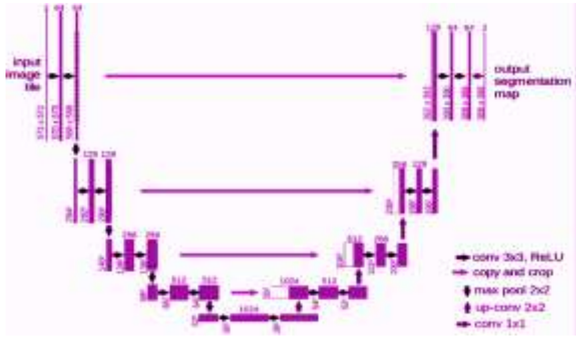

Fig.7. U-Net Architecture - Image Source [19]

Covid Severity Prediction

The disease transmissibility rate of Covid 19 is rapid causing a great challenge to the frontline workers. The limitations in life support equipment took the last breath of many lives. Severity prediction is crucial to categorize the patients in different levels of containment zones. Patients in critical condition can be admitted to Intensive Care Units and be given utmost attention. The final phase of this research work focuses on severity prediction. Severity Score Calculation was performed as outlined in Fig.8.

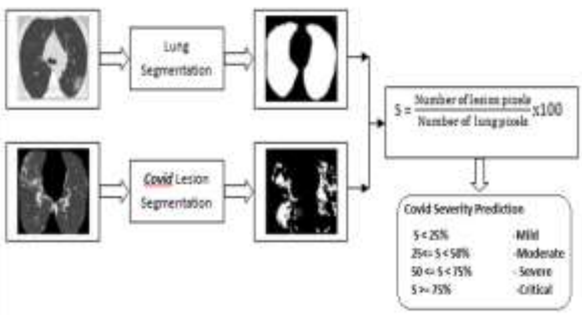

Fig.8. Phase 3-Covid Severity Range Prediction

Experimental Setup

Implementation of the Classification and the segmentation models were done implemented using Tensor Flow and Keras API with Python 3.7 on Intel® Core TM i7-7500U CPU @2.70Ghz,2901 MHz, and 64 GB RAM, with an 8-GB NVIDIA® card. To perform

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regularization and prevent over fitting during the training phase, a callback routine that performs early stopping was incorporated. The training will end abruptly if there is no change in the validation loss for the specified number of epochs.

V. Results and Discussion

We have used 200 train images (100 +ve samples and 100 -ve samples) and 60 images to test the Resnet-U-Net model. Clearly, the model is built with balanced class samples and Accuracy is chosen as the Evaluation metrics. We have achieved a validation loss of 0.168 and an segmentation accuracy of 96% when trained on 200 images for 30 epochs. Table 1 provides the training progress and tuned hyper-parameters results for the lung and lesion segmentation models. Table 2 exhibits the learning curve during the model training phase. It is perceived from the curves that, plot (g) has the most consistent and persistent curves that delivers the highest training and validation accuracy. Taking together as in Table 3, the findings suggest that the proposed framework proves to be robust in Covid Severity Range Prediction.

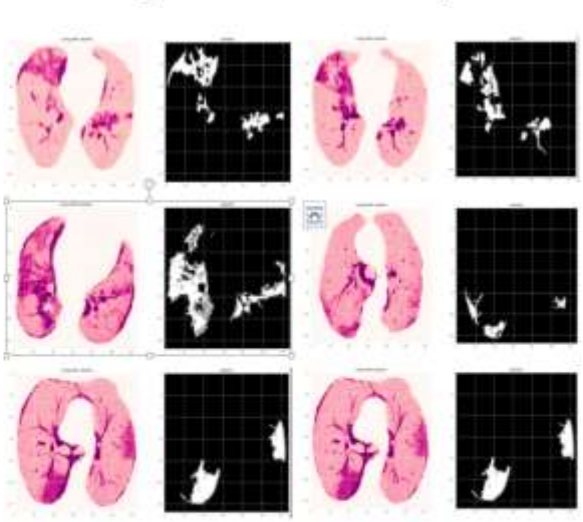


Fig. 9. Snapshot of : (A) Training Images with its GGO. (B) : Validation Images with its GG

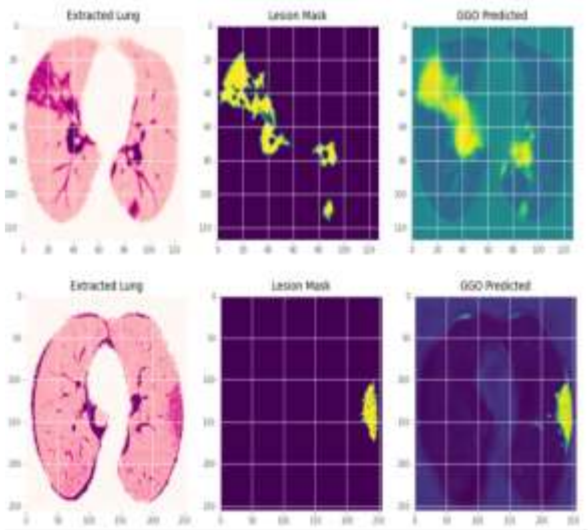


Fig.10. Phase 2: Lesion Segmentation Using ResNet-UNET

TABLE 1 QUANTITIVE ANALYSIS BY VARYING THE DIFFERENT HYPERPARAMETERS OF RESNET-UNET

Kernel Size	Batch Size	n_filters	Kernel Initializers	Validation Loss & Accuracy	DropOut	Epochs	Stride
3	16	16	he_normal	0.4971630275249481, 0.8930943608283997	0.1	30	2,2
3	16	32	he_normal	[0.1680331975221634, 0.96982210087776184]	0.1	30	2,2
3	32	16	he_normal	[0.7666683197021484, 0.410306304693222205]	0.1	30	2,2
5	16	16	he_normal	[0.6168349385261536, 0.8304417729377747]	0.1	30	2,2
3	16	32	random_normal	0.7741910815238953, 0.7797927856445312	0.1	30	2,2
3	16	32	trunc_normal	[0.6655519008636475, 0.8608983159065247]	0.1	30	2,2
3	16	32	he_normal		0.2	30	2,2

TABLE 2 MODEL LEARNING CURVES - TRAINING LOSS VS. VALIDATION LOSS

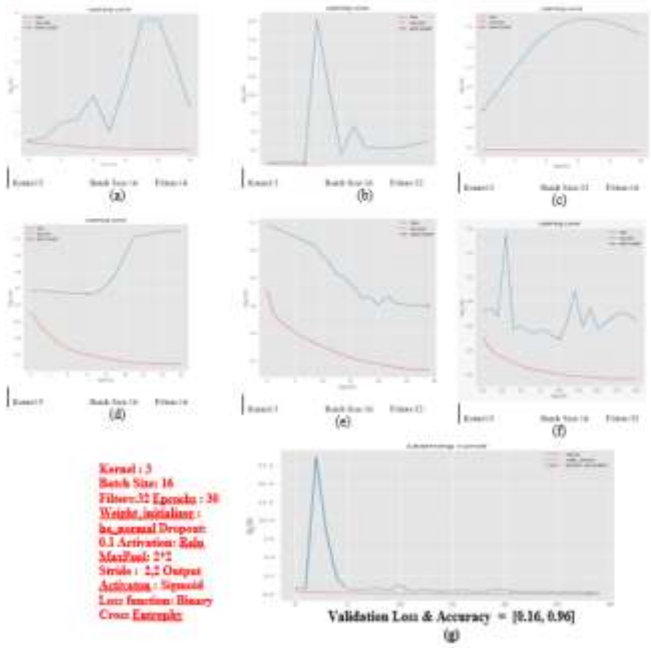
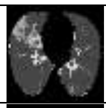
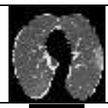
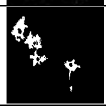
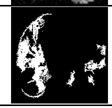


TABLE 3 RESULTS OF RESPIRONET-COVID SEVERITY PREDICTION FRAMEWORK

Lung Extraction using SegNet				
GGO Segmentation using RESPIRONET				

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Severity Score Prediction(SSP) Severity Range Prediction (SRP)	SSP=11 % SRP=mild	SSP=3.12% SRP=mild	SSP=50.03% SRP=severe	SSP= 40.679% SRP=moderate

Comparison with prior work on COVID Classification

We compared our proposed methodology with other similar approaches on COVID-19 classification from the literature and the results are clearly furnished in Table 4. Jin et al. [21] adopted a 2D CNN for segmentation of CT slices and trained a model for Covid-19 or normal classification. They investigated two public datasets LIDC-IDRI [20] and ILD-HUG [22] together with 496 positive and 260 negative samples from Wuhan Union Hospital. The system achieved an accuracy of around 97.9%. Singh et al. [23] fabricated a CNN based COVID-19 prediction model on multi-objective differential evolution. The resulted model could outperform the ANN-based models. Ahuja et.al [24] enhanced the performance of classification with Data Augmentation techniques and evaluated the pretrained models ResNets 18, 50, 101, and Squeeze Net for classifications. The results with a 0.99 AUC score prove the efficacy of ResNet18 compared to other models. Barstugan et al. [25] tried various statistical and wavelet-based feature extraction methods and classification by Support Vector Machine. GLSZM coupled with SVM yielded an accuracy of 99.68 %. Wang et al. [26] performed lung region extraction with pretrained UNet. The lung images of patients admitted to Renmin Hospital, China. They segmented the image with UNet ++ for Covid prediction with an accuracy of 92.5 %.

TABLE 4 COMPARISON WITH OTHER PRIOR WORKS ON COVID CLASSIFICATION

Ref.	Image Samples	Method	Accuracy
Jin et al. [23]	496 +ive, 1385 -ive	CNN	97.91 %
Singh et al. [25]	N/A	CNN	90%
Ahuja et.al [26]	349 +ive,397 -ive	ResNets 18, 50, 101 ane SqueezeNet	99.65%
Barstugan et al. [27]	53 +ive , 97 others	Feature Extraction coupled with SVM	98.7%
Wang et al. [28]	313 +ive, 229 -ive	UNET++	98.85%
RESPIRONET (Proposed Method)	**100 +ve ,100 -ve**	**Custom CNN (Lung Segmentation) and ResNet-UNET(Lesion Segmentation)**	**98.9 %**

Comparison with prior works on COVID segmentation

For further analysis of the outcome, the proposed framework is compared with other related approaches for Covid 19 segmentation and the results are tabulated in Table 5. Ma et al [35] adopted standard UNET 20 3D CT slices and attained 0.608 accuracies. Dominic et. al [38] further enhanced the approach on the same dataset using an inverted distribution on k-fold-cross-validation. Yan et al [37] designed a unique architecture for COVID segmentation and achieved better results around 0.73 accuracies. Saood et al [36] combined SegNet and U-Net. They trained the network nine times using different hyper parameters and obtained an accuracy of 0.749 %. Qiu et al [34] developed a lightweight CNN with limited parameters of 83K that would be easy for deployment in real-time.

TABLE 5 COMPARISON WITH OTHER PRIOR WORKS ON COVID SEGMENTATION

Ref.	Method	Training Dataset (Sample size)	Validation (Sample size)	Validation Accuracy
Amyar et. al[28]	U-Net (Standard)	1219	150	0.78
Fan et. al [29]	Inf- Net (Attention U-Net)	1650	50	0.76
He et. al[30]	M 2 UNet	666	666	0.759
Qiu et al[31]	MiniSeg using (Attention U-Net)	3558	3558	0.778
Ma et al[32]	Standard U-Net	20	20	0.608
Saood et.al.[33]	SegNet	80	20	0.749
Yan et. al [34]	COVD SEGNET	731	130	0.726
Dominik et. al[35]	Standard U-Net	20	20	0.804
RESPIRONET	**ResNet U-Net**	**200**	**60**	**0.960**

VI. CONCLUSION

In this research contribution, a deep neural network architecture RESPIRONET was developed. The model is carefully crafted based on full convolution architecture. Initially, the lung extraction segmentation model was built through a custom SegNet. Bayesian Optimization was used to search for the optimum hyper parameters based on 5-fold cross-validation. Subsequently, an improved and efficient U-NET model was built for GGO segmentation. We have used Resnet18 as the pre-training model in the encoder path of the U-NET architecture, thus enhancing the prediction results through transfer learning. Furthermore, dilated kernels were used for convolutions to improve the prediction accuracy. The framework also helps to assess the severity range of COVID as mild or moderate or severe or critical. We have achieved good segmentation results on the SARS-CoV-2 CT dataset. The framework predicts covid severity with the segmentation accuracy of 98.9% from CT scan images. Though significant improvements are obtained with the proposed model, larger and more diversified datasets are needed to build a generalized model that fits the realistic scenario. Cross dataset analysis, integrating the clinical parameters with the imaging outcomes, and scrutinizing the lung region hierarchy can be considered to be the future expansion of the work.

DATA AVAILABILITY

The SARS-CoV-2 CT scan dataset is available at: www.kaggle.com/plameneduardo/sarscov2-ctscan-dataset

DECLARATION OF COMPETING INTEREST

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The authors have no competing interests to declare that are relevant to the content of this article.

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