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Evaluation of Deep Architectures for Automatic Lung Infection Segmentation of COVID-19 HRCTImages

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Abstract—Deep learning has been one of the widely used techniques in biomedical image segmentation. COVID-19 is spreading rapidly all over the world. Early diagnosis of disease is necessary to control the pandemic. The common method of diagnosis of COVID-19 infection is RT-PCR (Reverse Transcription - Polymerase Chain Reaction) method. However, RT-PCR is prone to produce a number of false results and availability of RT-PCR kits is limited. Computed Tomography (CT) and X-Ray of lung can be used as an alternative tool to make the diagnosis, as the disease primarily targets the epithelial cells of the lung. The CT scanners considered to be diagnostic tools for COVID-19. The number of images to be analyzed by the radiologist is large therefore it is necessary to automate the task of CT Image processing. In this paper, we have developed an Automatedbiomedical segmentation system using five different deep learning architectures which performs the COVID-19 lung infection segmentation. The models are trained using open source datasets. Five deep learning models selected for study are U-Net, LinkNet, ResU-Net, ResU-Net++ and U-Net++. The U-Net++ model shown better results with a dice coefficient of 84.69%, sensitivity of 78.92%, specificity of 99.51% and precision of 92.12%. Experimental results are generated using PSG IMSR (Institute of Medical Sciences & Research) dataset, which is a collection of 75,000 images of nearly 125 patients. The radiologists have verified the results of infection segmentation. Automated infection segmentation of HRCT scans using deep learning modelscan be used for faster diagnosis of COVID-19.

Impact Statement — RT-PCR method used for COVID-19 infection diagnosis is prone to produce a number of false results and the availability of a number of RT-PCR testing kits is limited. Medical imaging like chest CT scan can be used as alternative tool as the disease primarily targets lung. Due to wide availability of CT scanners, they are considered to be diagnosis of COVID-19. The number of patients who undergo scans and images to be analyzed by the radiologist is very large therefore it is necessary to automate the task. Deep learning approach can be used effectively to aid the Radiologists and Physicians. We have

proposed deep learning based automated system which can greatly reduce the time in analyzing HRCT lung images of patients to ensure proper treatment to the needy patients. The system can assists in monitor the progress inpatients recovery by comparing the infection present in the lung.

This paper has been submitted on 14-July-2021. This project work is carried out as part master program in Computer science and Engineering.

Index Terms— Biomedical imaging, Convolutional Neural Network, Deep Learning, DICOM, Image Segmentation, SupervisedLearning

1. INTRODUCTION

Biomedical image segmentation is a process to identify organs or lesions from CT or MRI images in order to deduce vital information about organs like shapes and volumes. Previously, this process was performed using conventional approaches like edge detection filters and mathematical methods. Deep learning has become a matured technique over the years, and it has demonstrated significant capabilities in the field of medical image processing. The deep learning models are used to automate the biomedical image segmentation from CT scans or MRI images.

The ongoing CoronaVirus Disease 2019 (COVID-19)is spreading rapidly and the World Health Organization (WHO) declared COVID-19 as a pandemic outbreak in March 2020 [19]. COVID-19 predominantly affects the respiratory system. The common symptoms reported by COVID-19 patients are Fever, cough, difficulty in breathing, fatigue, body aches, loss of taste, sore throat, vomiting and Diarrhea. These symptoms are noticed between 2 and 14 days after virus infection [20].

Currently, there are two commonly used methods for COVID-19 diagnosis. First method is viral testing based on real time reverse transcription - polymerase chain reaction (rRT- PCR) for detecting viral RNA fragments in swabs taken from the nose or nasopharynx of infected patients. The other method is diagnosis based on imaging features on scans of computed tomography (CT) or chest X-rays. The effectiveness comparison between the two diagnosis methods is carried out and it has been concluded that chest CT has a faster and reliable detection. RT-PCR tests tend to report negatives at the initial stages of COVID-19 [3].

Most of the hospitals have CT image equipment whichcan be effectively used for COVID-19 diagnosis. However, the

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process of analyzing large numbers of CT scan images is time consuming. They need to analyse the features on the CT lung images to investigate the infection caused COVID-19. The screening of patients is an urgent task to quarantine infected patients at an early stage to ensure infected cases are kept under quarantine and treated appropriately . Deep learning techniques can be effectively used in automating the task of analysis of CTimages for COVID-19 diagnosis. The HRCT lung image segmentation and assessing infection involved can be automated using deep learning (DL) architectures. We have performed a detailed study of five different deep learning segmentation models and COVID-19 dataset containing a large number of CT scan images is used.

The terms and terminologies used throughout the paper are described in section II. The summary of research papers, journals and datasets that are referred to during our research work is provided in section III. Architectural details of deep learning models are provided in section IV. Section V provides the details of COVID-19 case study which includes system architecture, data preprocessing, workflow and training setup. Details of the deep learning models training outcome and experimental results generated using those models are described in section VI. The pros and cons of deep learning models and CT imaging for COVID-19 diagnosis is discussed in section VII. This chapter also compares the results obtained from different papers in COVID-19 infection segmentation. Outcome of our study on automatic infection segmentation using deep learning is summarised in chapter VIII.

2. TERMS AND TERMINOLOGIES

The reader needs to perceive the terms related to the paper. For their proper understanding the terms and terminologies are described.

Image Segmentation: Image Segmentation is the task of extraction of a lesion volume based on image analysis.

DICOM: One of the widely used standards for medical imaging to communicate and manage medical imaging data is Digital Imaging and Communications in Medicine (DICOM). Medical imaging equipment like CT scanners, MRI use the DICOM standard.

Coronavirus disease (COVID-19): Coronavirus is a newly identified virus causing infectious Coronavirus disease (COVID-19).

High Resolution Computed Tomography (HRCT): Its a type of Computed Tomography (CT) technique used for enhancement of image resolution.

Hounsfield Units (HU): Hounsfield Units used in computed tomography (CT) scanning is a dimensionless unit used to express CT scans in a standardized form.

3. RELATED WORKS

Deep learning researches in the field of segmentation of CT images are studied. Few references are made and the content of the paper works are summarized in this section.

[6] proposes an artificial intelligence (AI) system for computing scores for COVID-19 patients using images of chest CT scans. The CT scans scoring is performed fully automatically using three deep learning algorithms viz Segmentation of Pulmonary lobe, Segmentation of Lesion and Prediction of severity score and Prediction of CO-RADS score. The Lobe segmentation is performed in Two-stages. The CT severity score prediction is carried using the nnU-Net framework, which is based on U-Net architecture. The 3D Inception architecture is used for prediction of CO-RADS score.

[7] proposes an automated system for lung segmentation using deep learning. The model is trained to predict the infection in the lung due to COVID-19. The VB-Net is used for infection identification which is present in the regions of lung CT scans of COVID-19 patients CT images. Human in loop method is exercised for assisting radiologists in order to improve automatic annotation. The proposed human in loop model takes only a few minutes to perform the delineation of HRCT lung images as compared to several hours of time for a fully manual delineation process.

[5] proposes a fully automated high-speed approach to detect COVID-19. The dataset containing the HRCT scan images are in DICOM format. The system converts the 16 bit DICOM grayscale images to TIFF format. This TIFF image contains only image data and all private information of the patients are removed in the process of DICOM to TIFF conversion. The data is processed in two stages. In Stage 1, images with no infection are observed or the images which have dark pixels are discarded. In stage-2, classification of images is performed using the Feature pyramid network with ResNet50V2 Convolution Neural Network (CNN).

[8] proposes an Artificial Intelligent system that can diagnose Novel Coronavirus Pneumonia

(NCP). This system can also differentiate NCP from other types of pneumonia cases. The system assists radiologists in performing a quicker diagnosis when a large number of cases are reported due to pandemic situations. The common pneumonia datasets include the viral, bacterial and other types of pneumonia. The COVID-19 diagnosis system using Artificial Intelligent consists of two models. The first model can identify the lesion in the lung using segmentation. The second model performs the classification to achieve the for diagnosis. The system differentiated NCP from pneumonia and normal patients. The performance of the models are measured using sensitivity, accuracy and specificity.

[9] proposes a system for building a segmented CT dataset. This is achieved by fixing the errors and removal of noise information present in a HRCT lung scan dataset. The dataset contains three classes: normal patients (Normal), common pneumonia (CP), and novel coronavirus pneumonia (NCP). The processed dataset is used for benchmarking and comparing the performances of 3D and 2D convolutional neural networks (CNNs). The results showed that 3D CNNs performed better than the 2D CNNs models. The DenseNet3D121 and ResNet3D34 models achieved highest accuracies among all the convolutional neural networks (CNNs). The performance of the models are compared using accuracy, F1 score and AUC.

[10] provides insights of performances of various CNN models in classifying the COVID-19 patients using HRCT images of lungs. Ten different convolutional neural networks (CNN) are used to distinguish between the COVID-19 from non-COVID- 19 patients. The convolutional neural networks (CNN) used for evaluations are ResNet50, MobileNetV2, VGG16, AlexNet, SqueezeNet, ResNet101, GoogleNet, ResNet18, VGG19 and Xception. The Xception and ResNet101 are performed better than all other CNN models. The parameters like AUC, specificity , accuracy and sensitivity are used to compare the performances of the CNN models.

[11] provides insights of changes in chest CT findings of COVID-19 patients starting from initial diagnosis till the recovery of the patient. The chest CT repeatedly performed on the patient at approximately four day intervals. The lung lobes were visually scored on a scale of 0 to 5 after performing the HRCT scan of COVID-19 patients. The value 0 indicates the no involvement of the infection in the lung due to COVID-19 whereas the 5 indicates more than 75[\%] involvement of lung infection. The study observed that maximum lung involvement peaked at approximately 10 days from the initial symptoms observations. The paper shows that chest CT can effectively be used in monitoring the progress of COVID-19 patients.

[12] proposes a deep learning model to perform image segmentation of biological microscopy images. The model U- Net is composed in two parts: a contraction part and an expansion part. The first part is responsible for extracting image features. Second part of the network is used for localisation. The number of parameters of the U-Net is reduced as the model does not use any fully connected layer. The U-Net architecture can be trained with a smaller dataset.

[1] provides insights of the RT-PCR method for COVID-19 diagnosis and details of steps involved in performing RT-PCR tests. The workflow involved in detecting the COVID-19 is described starting from collecting the samples to finding the results of test samples.

[3] provides contrast between HRCT scans and RT-PCR methods in terms of consistency and diagnosis in COVID-19. The study is based on datasets of COVID-19 obtained from Wuhan, China. The assessment of HRCT in COVID-19 diagnosis performed by considering RT-PCR as an reference. Chest HRCT CT may be considered as a reliable diagnosis method for COVID-19 detection in areas of widespread occurrence.

[4] proposes various steps that need to be followed for executing Radiology projects using deep learning. The paper describes starting from defining specification to system deployment. Detailed use cases pertaining to deep learning projects which involve teams from different

streams are explained in this paper. This paper also explains about collecting the data, selections of models and selection of hardwares. The practical guidance that can be adapted foranalysis of medical images using DL is elaborated.

From the literature studies we have found that the deep learning models can effectively be used in segmentation of CT images for COVID-19 diagnosis. The major advantage of using these techniques over RT-PCR is reliability and quick analysis. Deep learning approaches can also reduce the screening time as compared to manual processing of images by expert radiologists. Based on availability of limited resources (both computing and time) and datasets, a suitable deep learning model needs to be identified for infection segmentation. Therefore we have studied various deep learning architectures to identify suitable models based on performance metrics like dice coefficient, sensitivity, specificity, precision and time required to train a network.

UNITS

The following deep models are considered for biomedicalimage segmentation studies:

A. *U-Net [12]*
B. *LinkNet [15]*
C. *ResU-Net [16]*
D. *ResU-Net++ [17]*
E. *U-Net++ [18]*

A. *U-Net Segmentation Model*

The U-Net is a Biomedical Image Segmentation model developed by Olaf Ronneberger et al [12]. The 3 parts of U-Net architecture are Contracting path (encoder) , expanding path (decoder) and the decoder. The image context is captured by the encoder and it has been implemented using convolutional and max pooling layers. Localisation is achieved using transposed convolutions in the decoder. The U-Net can be trained using few training samples but it provides good performance in image segmentation tasks.

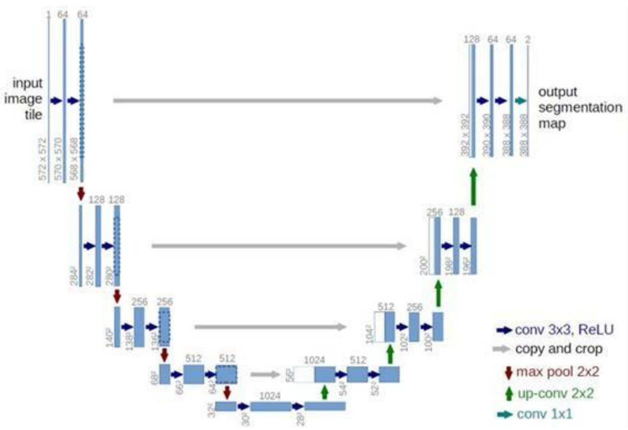

Fig. 1. U-Net Architecture [12]

B. *LinkNet Segmentation Model*

The LinkNet is an one more Biomedical Image Segmentation model developed by Abhishek Chaurasia et al in 2017 15].

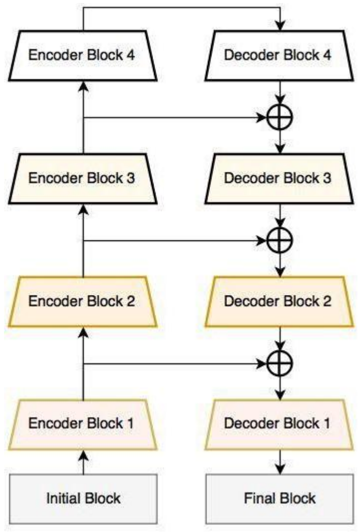

Fig. 2. LinkNet Architecture [15]

The main purpose of developing the LinkNet model is for efficient usage of limited resources for deep learning based image segmentation. LinkNet is a lightweight network as compared to U-Net architecture therefore training is faster. The LinkNet architecture consists of a series of encoder and decoder blocks. These blocks are used to break down the image and build it back up. The structure of the network is designed for faster training by a minimum number of parameters.

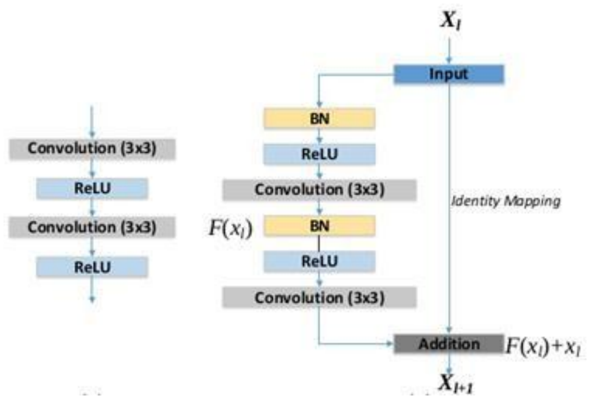

Fig. 3. Basic Building Block of ResU-Net [16]

C. *ResU-Net Segmentation Model*

The basic building block of ResU-Net is the residual unit. The Residual units consist of Two 3x3 convolutional blocks and An identity mapping. The Identity Mapping connects the input and output of the Residual unit. The Convolutional block consists of one unit of Batch Normalization layer, ReLU Activation layer and Convolutional layer. The residual unit of the basic building block used in ResU-Net is given in Fig 3. The 3 parts of ResUNet are Encoding, Decoding and bridge. In encoding units, a stride of 2 is applied to the first convolution block to reduce the feature map by half. Before each decoding unit, there is an upsampling of feature maps from lower level and a concatenation with the feature maps from the corresponding encoding path. At last a 1x1 Convolution is applied with Sigmoid activation to obtain a desired segmentation map. The complete architecture of ResU-Net is given in Fig 4:

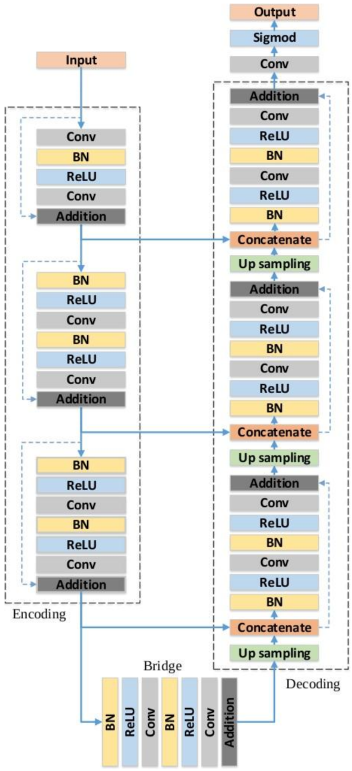

Fig. 4. Complete Architecture of ResU-Net [16]

D. *ResU-Net++ Segmentation Model*

The *ResU-Net*++ was developed by Debesh Jha et al for Biomedical Image Segmentation in the year 2019 [17]. The ResU-Net++ architecture is based on the Deep Residual U-Net (ResU-Net), which is an architecture that uses the strength of deep residual learning and U-Net. The ResUNet++ architecture takes advantage of the residual blocks, the squeeze and excitation block, ASPP, and the attention block. The residual block propagates information over layers, allowing to build a deeper neural network that could solve the degradation problem in each of the encoders. This improves the channel inter- dependencies, while at the same time reducing the computational cost. The ResU-Net++ architecture contains one stem block followed by three encoder blocks, ASPP, and three decoder blocks. The block diagram of the proposed ResU- Net++ architecture is shown in Figure 5. In the block diagram, we can see that the residual unit is a combination of batch normalization, Rectified Linear Unit (ReLU) activation, and convolutional layers.

E. *U-Net++ Model*

The U-Net++ model is by Zongwei Zhou et al for Biomedical Image Segmentation [18]. The U-Net++ model is an enhancementto the original U-Net and it consists of 3 new additions:

- redesigned skip pathways highlighted by green color)
- dense skip connections highlighted by blue color)
- deep supervision highlighted red color

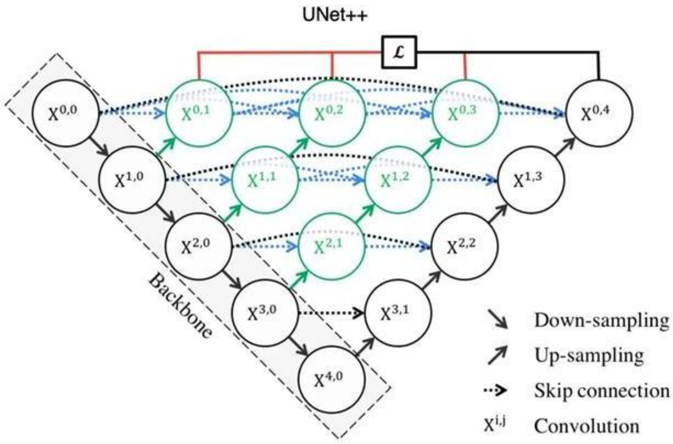

Fig. 6. U-Net++ Architecture [18]

The semantic gap between the encoder and decoder subpaths is bridged by the addition of redesigned skip pathways. The purpose of Dense skip connections is to improve segmentation accuracy and improve gradient flow and it also ensures that all prior feature maps are accumulated and arrive at the current node. Deep supervision is added to ensure the model can be pruned to adjust the model complexity and also to balance between speed & performance.

The comparison of deep learning segmentation models selected for our study in terms of architectural differences is given below:

TABLE I
ARCHITECTURAL DIFFERENCES BETWEEN MODELS

LinkNet	a) The improvement in LinkNet over U-Netarchitecture is faster training. b) LinkNet is a lightweight network compared toU-Net. c) The LinkNet consists of a series of encoderand decoder blocks to perform segmentation.
ResU-Net	The ResU-Net architecture is based on U-Net. b) The ResU-Net uses Residual Units as the basic building block instead of plain convolutionalblocks.
ResU-Net++	a) The ResU-Net++ architecture is based on ResU-Net. b) The ResUNet++ architecture takes advantage of the residual blocks, the squeeze and excitationblock, ASPP, and the attention block.

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U-Net++	The U-Net++ architecture is based on U-Net. b) The redesigned skip pathways added to bridge the semantic gap between the encoder and decoder subpaths. c) The dense skip connections are implemented between the encoder and decoder. d) The model can be pruned using deep supervision to balance between speed and performance.

CASE STUDY ON COVID-19 DIAGNOSIS

The case study selected for biomedical segmentation using deep learning is COVID-19 for automated biomedical image segmentation. The chest CT scan dataset used as input to the model. The open source dataset [21] [22] is used for training and validation of the models. The details of the open source dataset is given in table-II. The experimental results are generated using the PSG IMSR COVID-19 dataset.

A. System Architecture

The automated biomedical image segmentation consists of two main modules; Data Preprocessing and Segmentation Models. The input to the system is the HRCT lung images of COVID- 19 patients along with the corresponding ground truth masks of COVID-19 infection.

Model	Architectural Differences
U-Net[12]	a) Extension of a fully convolutional network forbiomedical images. Uses multiple upsampling layers. Skip connections. d) U-Net can give better performance with lessnumber of training samples.

Fig. 7. System Architecture

1) *Data Preprocessing*

The CT Image from PSG IMSR hospital is provided in DICOM (Digital Imaging and Communications in Medicine) format. The pixel values of DICOM images are 16 bit values ranging from -32768 to 32768. The value ranges in DICOM images correspond to the Hounsfield Scale. These images are preprocessed before preparing the training and test sets for training the deep models for HRCT lung image segmentation tasks.

The data pre-processing task involves the following steps:

i. Reading of CT Image: The HRCT images from PSG IMSR hospitals are in DICOM format. Pydicom Library is used to CT images in DICOM format and they are stored in arrays data type using numpy library.
ii. Pixels to Hounsfield Unit conversion: Pixels to Hounsfield Unit conversion is performed using pydicom library. HU indicates what tissue these unit values correspond to.
iii. Resampling: Resampling step is carried out to remove variance in scanner resolution. SimpleITK library is used for this process.
iv. Normalisation and Labelling: The input required for deep learning algorithms is between 0 to 1. Therefore, Normalisation is applied on each pixel value of the HRCT image as these pixels are in the Hounsfield Unit(HU). The labelling is performed to identify the class of CT image.

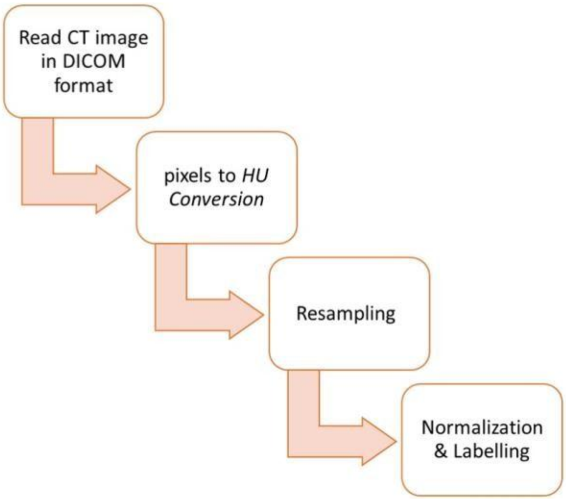


Fig. 8. Data Preprocessing of HRCT lung images

2) *Segmentation Models*
Segmentation Models are trained for predicting the infections involved in lungs due to COVID-19. The inputs required for training the models are lung CT image and corresponding ground truth mask. The process involved in training of segmentation models based on supervised learning methods for COVID-19 infection segmentation is depicted in Figure 9. The model is updated after the comparison between the predicted mask and ground truth.

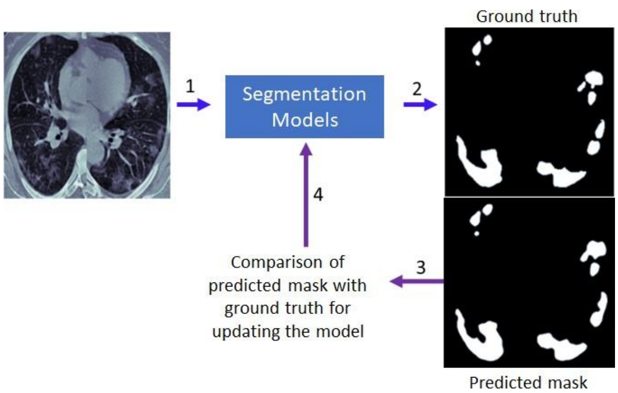


Fig. 9. Supervised learning of Segmentation Models

B. Workflow

The workflow involved HRCT Lung Image Classification is asfollows:

Data Preparation: The input CT image is processed in this step. The CT images are provided in DICOM image format and they are preprocessed as described in Figure 2. The dataset is split into a training set and validation set as required by the supervised learning of deep learning models.

Building Model and Hyperparemetrs: The implementation of model or importing of existing model carried out at the beginning of this stage. All key hyper parameters such as number of epochs, batch size, accuracy parameters, learning rate, model optimization methods are selected. The model is initialized based on the hyperparameters chosen and compiled. **Network Training:** All the models are trained training dataset and validated using valid dataset in this step.

Performance Measurement: Performance of the models are evaluated using a test set of images. The model performance isevaluated using dice coefficient, specificity, sensitivity and Precision. The results of performances of models are describedin section VI.

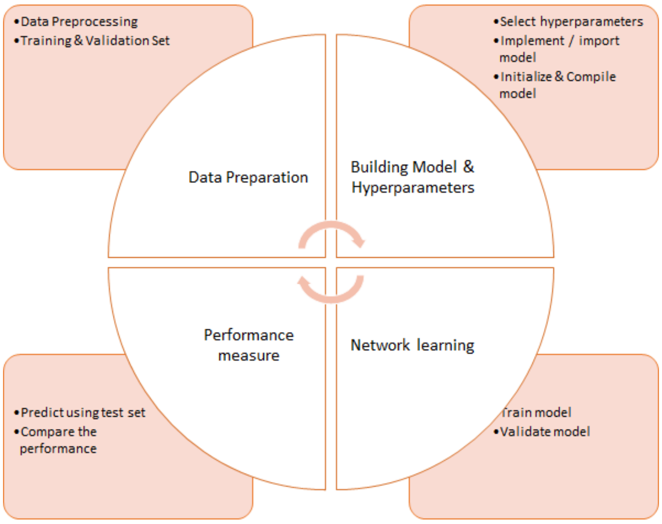


Fig. 10. Workflow of Image Classification

C. Dataset details

The dataset used for training and validation of the Model for segmentation is given Table II. This COVID-19 dataset is chosen from open source. Total 1921 images of COVID-19 patients are used for training and validation of the model. The dataset contains lung mask and infection mask for each image. These images were split into a training and validation with a split of 70\% and 30\% respectively. Total Number of images used for training the network is 1344 images. The network is validated using 577 images. The PSG IMSR dataset of COVID-19 patients is used to generate the experimental results from the trained deep learning segmentation models. The PSG IMSR dataset contains the 72550 CT lung images of 125 COVID-19 patients.

TABLE II
OPEN SOURCE COVID-19 DATASET

Dataset	cases	format	Mask data
COVID-19 CT Lung and Infection Segmentation Dataset[21]	20	Nifty	Yes
COVID-19 CT SegmentationDataset [22]	9	Nifty	yes

TABLE III
PSG IMSR COVID-19 DATASET

Dataset	cases	format	Mask data
PSG IMSR COVID-19 dataset	125	DICOM	No

D. *Training Setup*

The training of deep learning models requires Ground truth along with preprocessed lung images as input for learning. The training set is prepared from the COVID-19 HRCT dataset to train the DL based segmentation models. The optimiser used during the training is Adam. The metrics used for the evaluation of the model during the training are dice coefficient, Precision, specificity and sensitivity. The training of the network is done with a batch of 32 samples. Number Epoch used for the training is 100. Figure 11 shows the scheme of performing training of deep learning segmentation models.

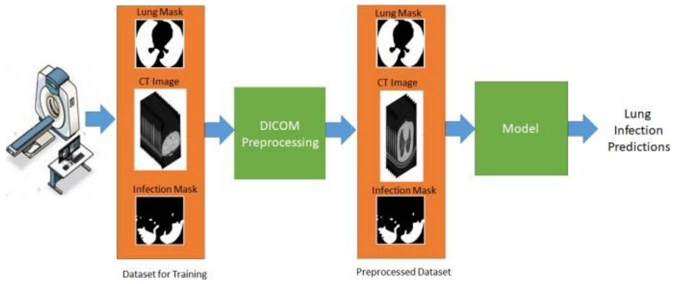


Fig. 11. Segmentation Models Training

4. EXPERIMENTAL RESULTS

Testing the system is an essential phase since it makes sure of the reliability and the quality of the application. Sensitivity,
Precision, Dice Coefficient and Specificity are used for evaluation of the models. Deep learning segmentation models belong to supervised learning since the training data of COVID-19 HRCT lung images. The ground truth masks are used for training the segmentation models and also to compute the dice coefficient. The validation set (577 images) from the open source dataset is used for evaluation of the models. Experimental results are generated using PSG IMSR COVID- 19 from the trained models and results have been validated by the

radiologists. The terminologies involved are:
True Positive: Observation is positive, and is predicted to be positive.
False Negative: Observation is positive, but is predicted to be negative.
True Negative: Observation is negative, and is predicted to be negative.
False Positive: Observation is negative, but is predicted to be positive.

Precision = True Positive / (True Positive + False Positive) Sensitivity= True Positive / (False Positive + False Negative) Specificity= True Negative/ (True Negative + False Positive)
*Dice Coefficient = (2 * True Positive) / (2* True Positive + False Positive + False Negative)*
The training outcome of the U-Net, LinkNet, ResU- Net, ResU-Net++ and U-Net++ models are shown in Fig 12, 13, 14, 15 and 16 respectively. The models are trained using HRCT lung images of COVID-19 patients and corresponding infection ground truth. All the models are trained for 100 epochs. The optimiser used is Adam. The batch size selected for training the network is 32.

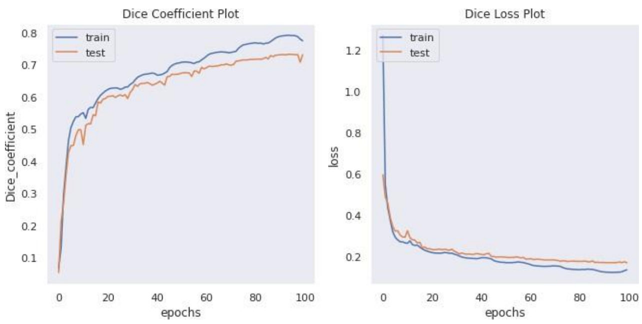
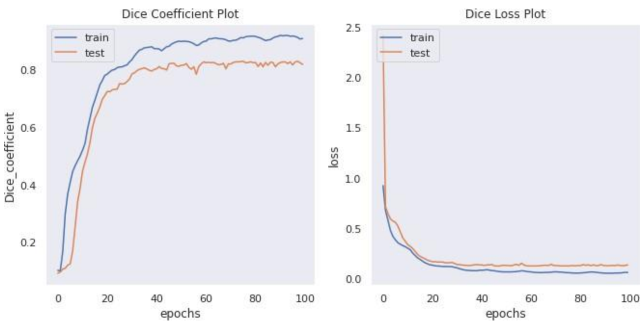


Fig. 12. Dice Coefficient & Dice Loss plot of U-Net Model



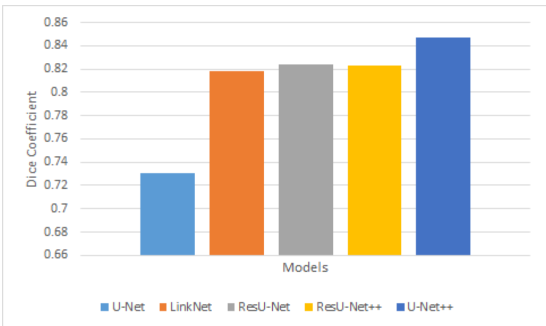


Fig. 13. Dice Coefficient & Dice Loss plot of LinkNet Model

Fig. 17. Dice Coefficient comparison between deep learning models

The performance of deep learning models are measured using Dice Coefficient, specitivity, sensitivity and precision. The performance of models for COVID-19 dataset is given in table-IV.

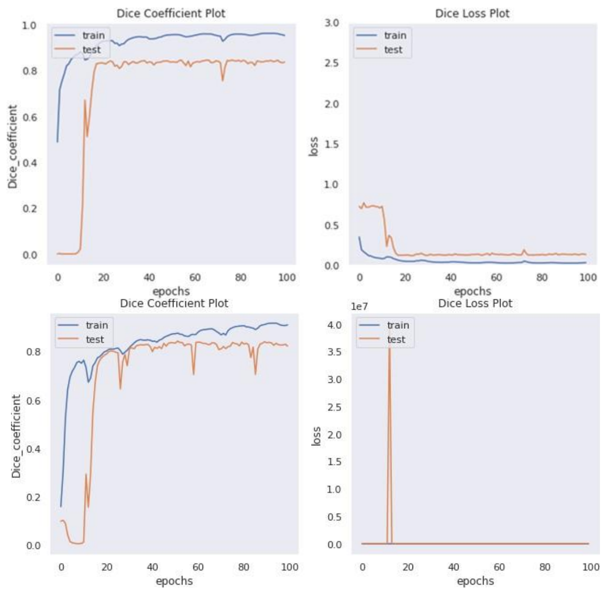


Fig. 14. Dice Coefficient & Dice Loss plot of ResU-Net Model

Fig. 15. Dice Coefficient & Dice Loss plot of ResU-Net++ Model

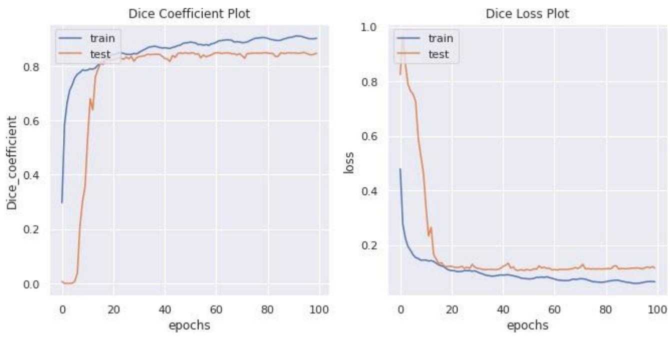


Fig. 16. Dice Coefficient & Dice Loss plot of U-Net++ Model

The dice coefficient comparison among all 5 deep learning models that have been used in our study is shown in Figure 17. The U-Net++ network got the highest dice coefficient of 84.69%. The next highest dice coefficient of 82.41% was seen in ResU-Net. The ResU-Net++ model has a dice coefficient of82.29%. The LinkNet and U-net have a dice coefficient of 81.78% and 73.07% respectively.

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TABLE IV
PERFORMANCES OF DEEP LEARNING SEGMENTATION MODELS

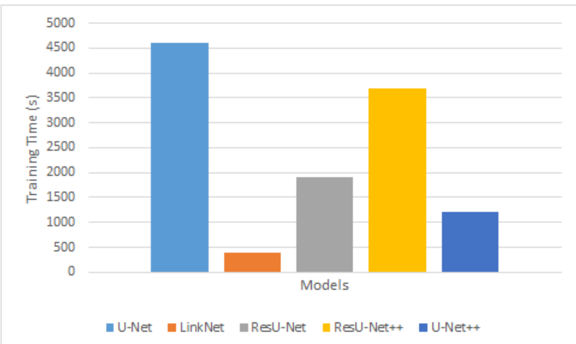
Model	Precision	Sensitivity	Specificity	Dice Coefficient
U-Net	92.38%	76.85%	99.54%	73.07%
LinkNet	93.86%	70.78%	99.66%	81.78%
ResU-Net	92.33%	74.51%	99.55%	82.41%
ResU-Net++	90.31%	75.56%	99.41%	82.29%
U-Net++	**92.12%**	**78.92%**	**99.51%**	**84.69%**

TABLE V
PSG IMSR COVID-19 DATASET

Model	Training Time (s)	Testing Time (s)
U-Net	4600	5
LinkNet	**400**	**1**
ResU-Net	1900	2
ResU-Net++	3700	4
U-Net++	**1400**	**2**

As shown in Table 5, we had analyzed the time taken by the models for training and testing for COVID-19 dataset. The models were trained and tested on the Graphics Processing Unit (GPU) Tesla K80 with memory of 12GB which is provided by the Google Colab. Google Colab development environment provides RAM capacity of 12GB and disk space of 25 GB. The training time includes the time taken to train the model for 100 epochs. Testing time is the time taken by the model to test 577 images to check the correctness of the model. The U-Net took 3900 sec for training and 1 sec for testing. The LinkNet model completed training in 400 sec and 1 sec for testing. The training and testing of ResU-Net was completed in 1900 respectively. The ResU-Net++ model covered 3700 s for training and 4 s for testing, whereas the U-Net++ model covered 1400 s for training time and 1 s for testing.
The graph shown in Figure 18 is a comparison of training time between 5 different deep learning models that have been used in our study. LinkNet took the lowest time of 400 sec to train the network. The second best performance is shown by the U- Net++ which completed the training in 1400 sec.

Fig. 18. Training time comparison between deep learning models



After the completion of training, the Models are tested using a test dataset of 577 images. The infection segmentation results are generated for the entire test dataset for all 5 different deep learning models. The results of infection are plotted along with CT image and ground truth for comparison. Few of the COVID-19 lung infection prediction results obtained from all 5 DL models for the test dataset are shown in Figure 19. The images of the original HRCT lung image and Ground truth are also shown for better visualisation.

The experimental results are generated from the trained deep learning segmentation models using HRCT lung images of PSG IMSR datasets for 25 patients. Figure 20 shows few of the experimental results using the PSG IMSR dataset which comprises the original lung image and the Infection prediction by the all 5 deep learning segmentation models.

Fig. 19. COVID-19 Infection predictions by five different deep learning models along with CT image and ground truth

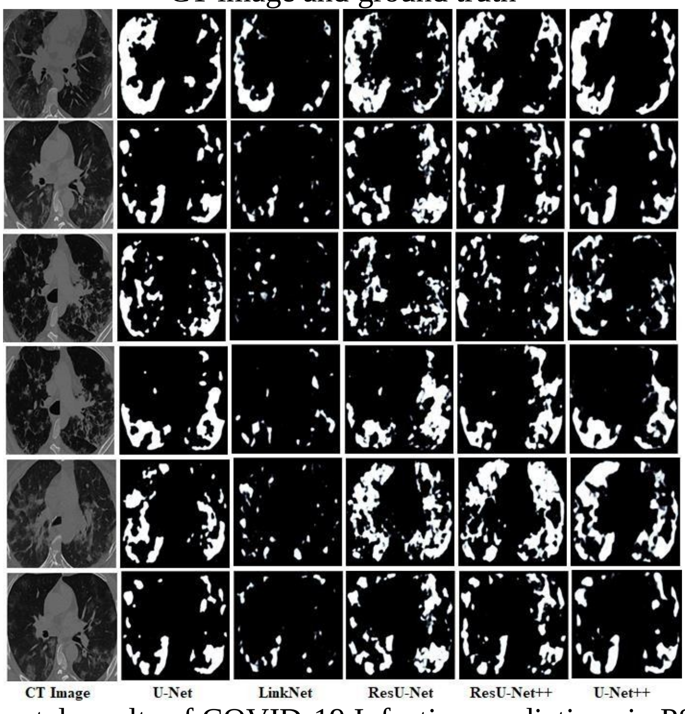


Fig. 20. Experimental results of COVID-19 Infection predictions in PSG IMSR dataset

5. DISCUSSION

Diagnosis of COVID-19 using HRCT scans is a more reliable method than existing RT-PCR. The results provided by the models are quick which helps in quarantining of patients. Early diagnosis generally increases the better treatment of the disease and control of pandemic. Patients exposed to radiation during CT scans may have some side effects. The radiation during CT scan is harmful to the pregnant ladies and for a person with metal implants. With an early diagnosis, this disease can be wrongly predicted therefore CT Scan screening results can be combined with RT-PCR lab tests. The deep learning approach can be used effectively to aid the Radiologists and Physicians as the large number of cases are reported during the pandemic. The accuracy of manual testing is better as doctors themselves analyse the images whereas the performance of the model depends on the dataset which is limited currently. The factor involved in CT scan based testing is the cost. The cost involved in CT scan is higher compared to RT-PCR testing.

Table VI provides the composition of our models with other segmentation models developed for COVID-19. All the above models predict the infection in the CT scan images of COVID-19 patients with different dice coefficients, specificity, sensitivity and precision according to the specific models.

TABLE VI COMPARISON WITH OTHER METHODS

Model	Precision	Sensitivity	Specificity	Dice Coefficient
FCN [23]	59.7%	71.9%	-	65.9%
V-Net [23]	60.3%	74.4%	-	62.5%
U-Net [23]	66.2%	73.6%	-	68.8%
COVID-SegNet [23]	72.6%	75.1%	-	72.6%
U-Net++ [23]	71.9%	73.5%	-	68.1%
U-Net [24]	-	53.4%	85.8%	43.9%
U-Net++ [24]	-	67.2%	90.2%	58.1%
Gated-Unet [24]	-	65.8%	92.6%	62.3%
Inf-Net [24]	-	69.2%	84.3%	68.2%
Attention-Unet [24]	-	63.7%	92.1%	53.8%
Dense-Unet [24]	-	59.4%	84.0%	51.5%
Semi-Inf-Net [24]	-	72.5%	96.0%	73.9%
Our COVID-19 study results				
U-Net	92.38%	76.85%	99.54%	73.07%
LinkNet	93.86%	70.78%	99.66%	81.78%
ResU-Net	92.33%	74.51%	99.55%	82.41%

ResU-Net++	90.31%	75.56%	99.41%	82.29%
U-Net++	**92.12%**	**78.92%**	**99.51%**	**84.69%**

APPENDIX

NILACKNOWLEDGMENT

models are trained with limited datasets available from open source, the performance of models can be further improved with larger datasets of COVID-19 HRCT scans.

The deep learning approach can be used effectively to aid the Radiologists and Physicians as the large number of cases are reported during the pandemic. This type of automated system can greatly reduce the time in analysing the large number of HRCT lung images of patients to ensure proper treatment to the needy patients. This system can also be used to monitor the progress in recovery of the patients by comparing the infection present in the lung. We believe that with the help of Deep Learning algorithms, the diagnosis of COVID-19 can be faster in isolation of COVID-19 patients to prevent pandemic and which in turn can help in saving human life.

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6. CONCLUSION

Our main objective is to study the different deep learning algorithms used for biomedical image segmentation and automate the process of infection segmentation of CT images using different deep learning networks for COVID-19 diagnosis. In our study, 5 different deep learning models are used for Segmentation. The models used for study are U-Net, LinkNet, ResU-Net, ResU-Net++ and U-Net++. These models are trained to predict the infection involved in the lungs of COVID-19 patients. The models are trained using a dataset available from open source [21] [22] which consists of both CT lung Images and corresponding ground truth infection masks. The U-Net++ model performed better among all models in terms of dice coefficient, specificity, sensitivity and precision. The time required to train is also less compared to U-Net, ResU- Net and ResU-Net++. The model achieved a dice coefficient of 84.69%, sensitivity of 78.92%, specificity of 99.51% and precision of 92.12% on test data. The experimental results are generated using COVID-19 HRCT dataset of PSG IMSR and these results have been verified by the radiologists. Since these

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