International Research Journal of Computer Science (IRJCS) ISSN: 2393-9842
Issue 07, Volume 08 (August 2021) https://www.irjcs.com/archives

COVID-19 CT SCAN IMAGE SEGMENTATION USING TRANSFER LEARNING APPROACH

Jaswant Singh Jothe
M Tech Scholar, Department of CSE
Madhav Institute of Technology and Science (MITS), Gwalior, India
Jaswantgsti@gmail.com
Punit Kumar Johari
Assistant Professor, Department of Information and Technology
Madhav Institute of Technology and Science (MITS), Gwalior, India
pkjohari@mitsgwalior.in

Publication History
Manuscript Reference No: **IRJCS/RS/Vol.08/Issue08/AUCS10091**
Received: 13, August 2021
Accepted: 21, August 2021
Published:25, August 2021
Citation: Jaswant & Punit (2021). COVID-19 CT SCAN IMAGE SEGMENTATION USING TRANSFER LEARNING APPROACH. International Research Journal of Computer Science, VIII, 200-208
doi: https://doi.org/10.26562/irjcs.2021.v0808.008
Peer-review: Double-blind Peer-reviewed
Editor: Dr.A.Arul Lawrence Selvakumar, Chief Editor, IRJCS, AM Publications, India

Abstract: The Computer tomography Scan imaging technique becomes an alternative approach of RTPCR test in COVID-19 diagnosis, disease staging and monitoring of treatment response evolution. The sensitivity of RTPCT is low neat about 70% with compare to the sensitivity of chest CT Scan images technique up to 98%. In this work, COVID-19 CT Scan image segmentation has been performed. The UNET Model has been selected as the baseline model for CT Scan Image Segmentation. The CT Scan Image segmentation performance of the deep learning models has been improved using the transfer learning approach. The IoU values have been improved from 86.94 to 88.90, 93.56, 94.34 using MobileNet as an encoder, DenseNet201 as an encoder, DenseNet169 as an encoder in Baseline UNET Models respectively.
Keywords: Image Covid-19 Scan CT

I. INTRODUCTION

The severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), initially reported in Wuhan, China in December 2019 [1],[2]. The coronavirus belongs to the family Coronaviridae. SARS-CoV-2 causes the current pandemic COVID-19. Globally, as of July 22, 2021, out of 192 million COVID-19 positive patients, 41.2 Lakhs patients have perished. Whilst, in India, out of 31.25 million COVID-19 positive patients, 4.18 Lakhs patients are perished [3]. India encountered the second wave of COVID-19 more devastating than the first wave. The most common variants during the second wave are found more virulent mutant variants such as Double Mutant (B.1.617), Triple Mutant (B.1.618), and The Delta variant (B.1.617.2) [4]. The Delta variant is mutated as Delta plus variant (AY.1). In the first wave, most of the patients whose age is above 65 years with comorbidities have a high risk of severe illness due to COVID-19. The highest CFR (Cases Fatality Rate) in the second wave is 3% in June 2021, and overall CFR is 1.31% one of the lowest in the country. Fig. 1 [5] depicts the CFR month-wise in India.

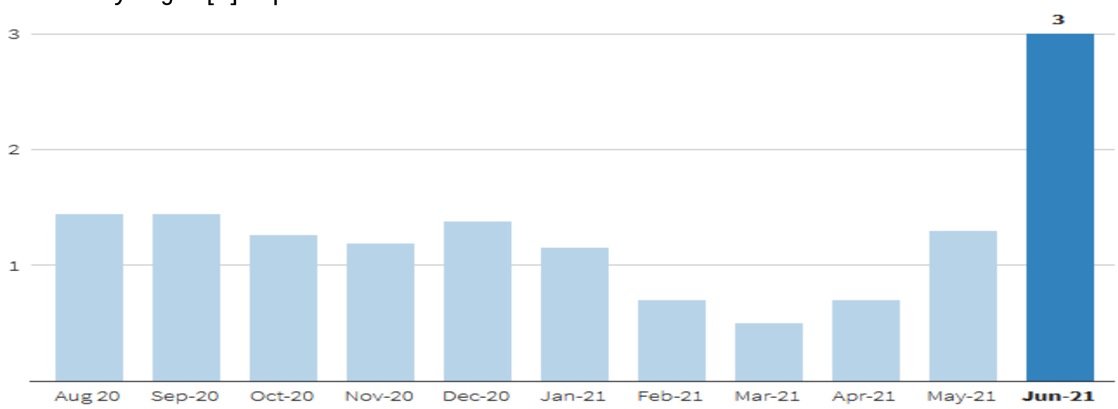


Fig. 1. CFR (Cases Fatality Rate) in India

R-value (effective Reproduction number) shows the rate of infection at which infection spread from one person to another. E.g. If R-value is 0.8 means 10 infected people spread the disease infection to another 8 people. If R-value is 1.20 means 10 infected people pass this infection to another 12 people. Fig.2 [6] depicts the R-value versus months in India. In Fig. 2, the maximum R-value is above 1.8. Whilst, the current (nearby 20th June, 2021) R-value of India is 1.17. If R-value is below 1, it indicates disease infection is reducing in trends and when R-value is above 1, indicates the disease infection spreading in trends. In India, at the starting of the current pandemic in mid-march 2020, the R-value is 2.4. The R-value is then reduced is around 1.7 between 4th to 16th, April and again R-value drops to 1.34 from 13th April to 15th May as a result of lockdown [7].

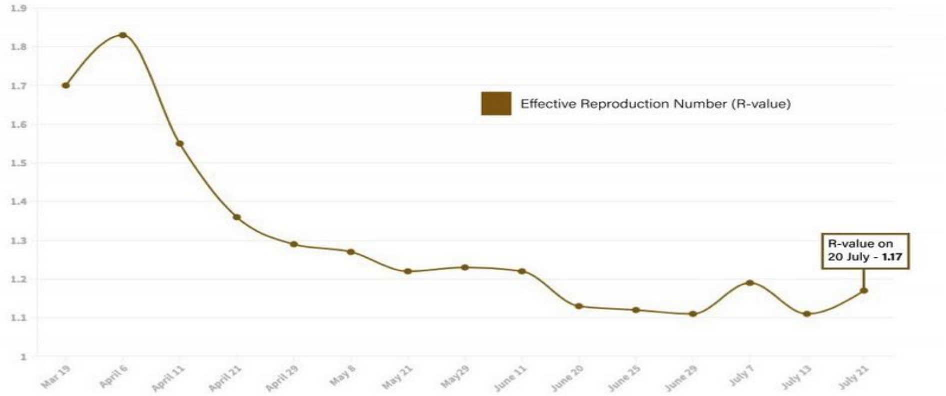


Fig. 2. The R- values in India

The mortality rate state-wise depicts in Fig. 3[6] in India. The mortality (death rate) is the rate at which deaths occur in a particular number of people. In fig. 3, Maharashtra, Madhya Pradesh and Delhi have a high rate of mortality followed by Gujarat state. Gujarat State has a maximum 4.38 mortality rate, Whilst, Ladakh has a minimum 0.17 mortality rate in India.

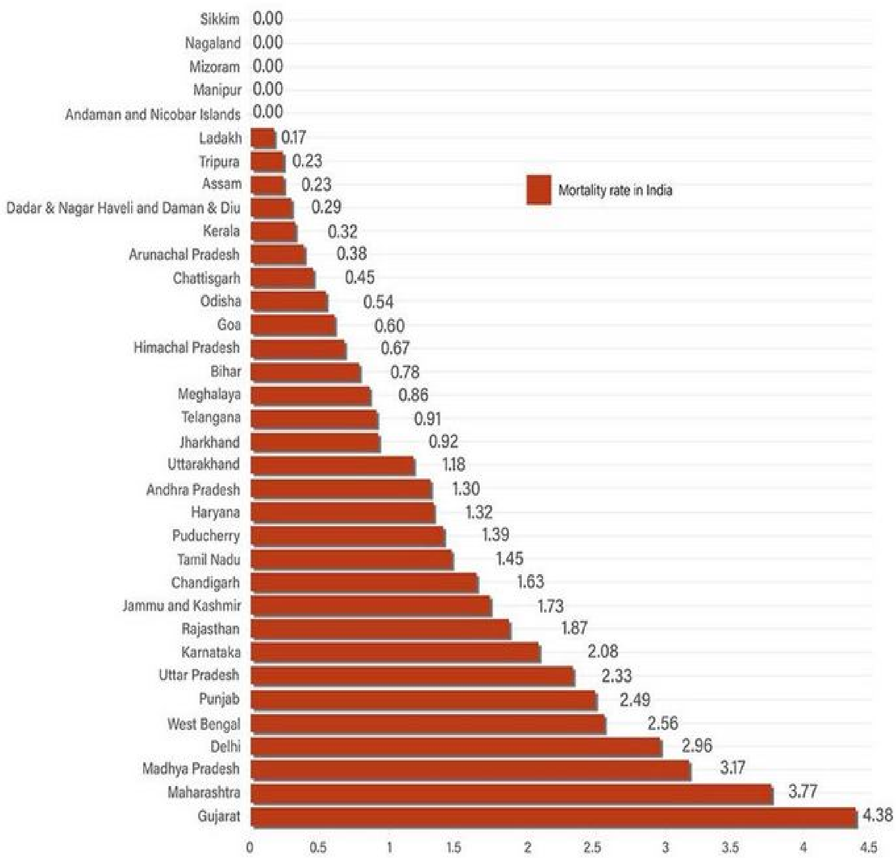


Fig. 3. Mortality Rate versus States

As of July 21, 2021, The high burden states likes Maharashtra, Tamil Nadu, Delhi, Karnataka, and Andhra Pradesh are depicted in table 1 [6]. In table 1 shows high burden states COVID-19 data such as states name, Confirmed cases, Recovered cases, Active cases, and Deaths.

TABLE 1- COVID-19 HIGH BURDEN STATES DATA

S. No.	States Name	Confirmed cases	Recovered Cases	Active Cases	Deaths
1	Maharashtra	3,18,695	1,75,029	1,31,636	12,030
2	Tamil Nadu	1,75,678	1,21,776	51,351	2,551
3	Delhi	1,23,747	1,04,918	15,166	3,663
4	Karnataka	67,420	23,795	42,222	1,402
5	Andhra Pradesh	53,724	24,228	28,800	696

II. METHODOLOGY

The Transfer Learning approach is used as methodology, where the image segmentation performance of the UNET Model (selected as baseline model) of COVID-19 CT Scan Image Segmentation has been improved using the Transfer Learning approach. The MobileNet, DenseNet201 and DenseNet169 are used as encoders in the UNET model for achieving the COVID-19 CT Scan image segmentation performance improvement. Following steps performed in used methodology

1. Download the COVID-19 CT Scan image segmentation dataset[8]. The dataset is in the form of a 3D volume file in Neuroimaging Informatics Technology Initiative (NIfTI) format. There are two files inside the dataset in NIfTI 3D volume format, one file contains the CT Scan images and another file contains the Ground Truth images.
2. Visualized and extracted the CT Scan images and their corresponding infection masks (Ground Truth Images) using slicer software version 4.11 from the 3D volume NIfTI format (.nii file extension) [9].
3. Manual cropping and resizing of the COVID-19 CT Scan 100 images with their Ground Truth images of 40 COVID-19 positive patients have been performed.
4. Manual labeling of the Ground Truth images has been performed using the proposed algorithm implemented in python language.
5. After that, applied the data augmentation techniques such as RandomRotatep90, Horizontal Flip, and Vertical Flip for generating more augmented CT Scan images and corresponding masks. Here, 1000 CT Scan images and its infection masks (Ground Truth images) are generated.
6. Splitting of the augmented images into Training Set, Validation Set, and Test set has been performed. The Training set contains 800 images, Validation Set contains 100 images, and the Test set has 100 CT Scan images with its infection masks (Ground Truth Images).
7. A training set is used to train the deep learning models, a Validation set is used to validate the DL models, and a Test set is used to test the DL models.

The pictorial representation of methodology is shown in Fig. 4.

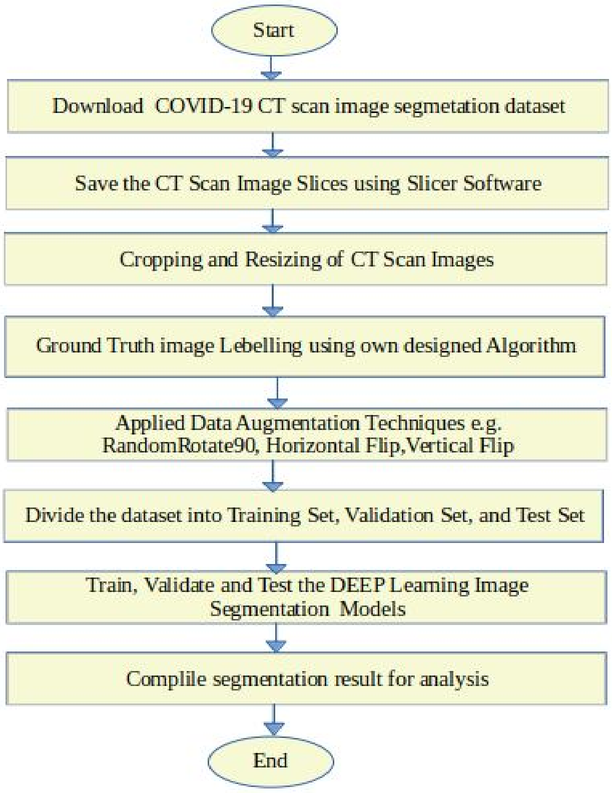


Fig. 4. Methodology Flow Diagram

In Fig. 4, the manual infection labeling was performed using the proposed algorithm implemented in python. After applying the infection labeling algorithm, every pixel has assigned the intensity value with their respective class of infection inside the input CT Scan images. Class 0 has all the background pixels with intensity value 0, Class 1 has all pixels of Ground Glass Opacity with pixel intensity value 1, Class 2 has all pixels of Consolidation with intensity value 2 and Class 3 has all pixels of Pleural Effusion with pixel intensity value 3. This manual infection labeling assignment process of CT Scan image pixels is very much required for training the deep learning models using Tensor flow library[10] and Keras library[11]. In the above-mentioned algorithm, the pixel-wise transformations have been applied. For data augmentation, the albumentations library [12] has been utilized. RandomRotate90, Horizontal Flip, and Vertical Flip data augmentation operations are applied for generation 1000 images with its corresponding infection mask or Ground Truth images. The dataset has been divided into the Training set contains 800 images, the Validation set contains 100 images, and Test Set contains 100 images and its ground truth images.

III. IMPLEMENTATION

The well-known UNET architecture model [13] is selected as the baseline model. The main objective of this work is to improve the COVID-19 CT Scan image segmentation using a transfer learning approach. The Deep learning pre-trained models such as MobileNet, DenseNet169 and DenseNet201 are applied as feature extractor encoders. Fig. 5 shows the implemented UNET model. The experimentations work has been performed using Google Colab [14].

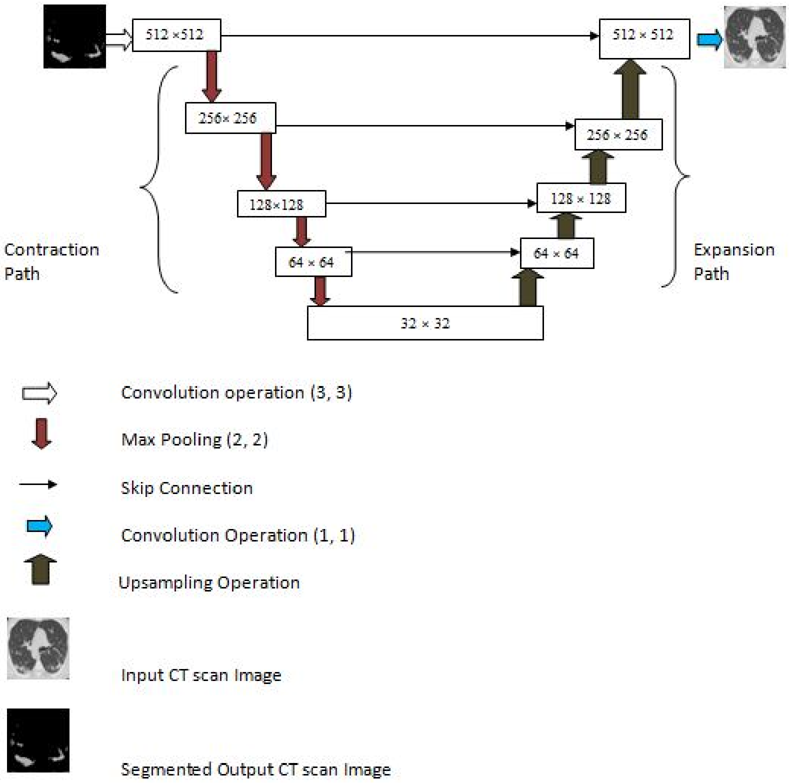


Fig. 5. UNET Model

Fig. 5 depicts the implementation of the UNET Architecture model. The UNET Model is invented in 2015, especially used for biomedical image segmentation. The UNET Model has two paths that are connected by a bridge block. The contraction path consists of four encoder blocks that are used as feature extractors in UNET Model. The bridge block is used for providing the connection between the contraction paths to expansion path. In the contraction path of the UNET Model, CT Scan image of size 512 × 512 × 3 takes as an input image to convolution block 1 and generates features maps of image size 256 × 256. These features maps are then used as input in convolution block 2 and generate the features map of image size 128 × 128. Further, the convolution block 3 takes the input of the features maps of image size 128 × 128 and passes generated features maps of 64 × 64 image size to convolution block 4. Convolution Block 4 is connected to Bridge convolution block with features maps of image size 32 × 32 and passes the output features maps to the expansion path. In the expansion path again four decoder blocks are present. Decoder block 4 is connected to the bridge convolution block via upsampling operation. Decoder block 4 is connected to decoder block3 via upsampling operation. Similarly, decoder block 3 is connected to decoder block 2 via upsampling operation and decoder block 2 is connected to decoder block 1. Features maps image size in expansion blocks are expanded 64,128, 256, and 512 of image size in decoder block 4, decoder block 3, decoder block 2, and decoder block 1 respectively.

(a) Transfer learning technique implementation

Deep learning models are trained on a big dataset such as ImageNet Dataset, COCO dataset with GPUs for many days training and got optimized the CNN weights of models. Transfer learning is a technique that facilitates to us with applications of pre-trained models in our problem domains e.g. multiclass COVID-19 CT Scan image segmentation. Fig. 6 shows the transfer learning approach implemented in this work.

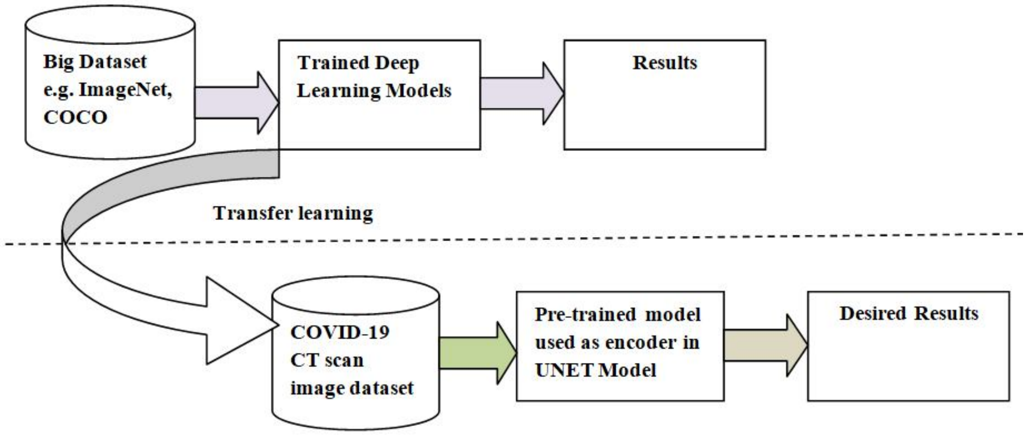


Fig. 6. Transfer learning applied in COVID-19 CT Scan image segmentation

(b) Parameter tuning

Deep learning models such as DenseNet169 [15] as encoder UNET Model and denseNet201 as encoder UNET Model are tuned with the parameter such as the batch size of 08 images and batch size of 04 images. Fig. 7 (a) depicts the performance graph of epoch versus IoU values and epochs versus dice coefficients values.

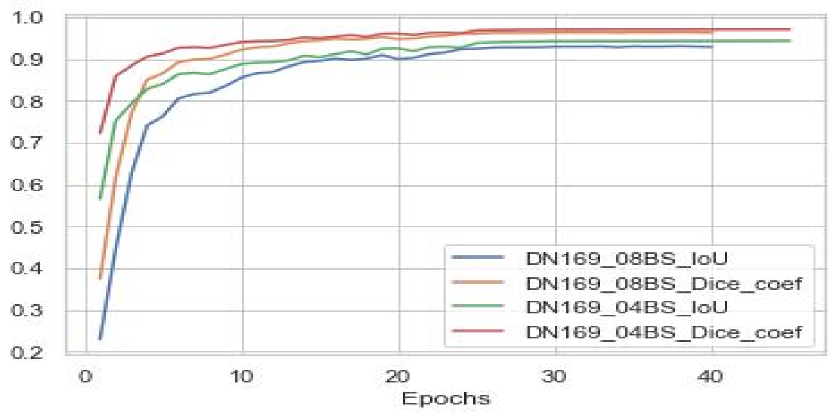


Fig. 7 (a) Epochs versus IoU values and Dice Coefficients values of DenseNet169 as encoder UNET Model

In above Fig. 7 (a), It is clearly shown that DenseNet169 as encoder UNET Model with a batch size of 04 images gives better performance. Therefore, DenseNet169 as encoder UNET Model with a batch size of 04 image size is selected for this work. Fig. 7 (b) represents the comparison performance with epochs versus IoU Values of DenseNet201 as encoder UNET Model.

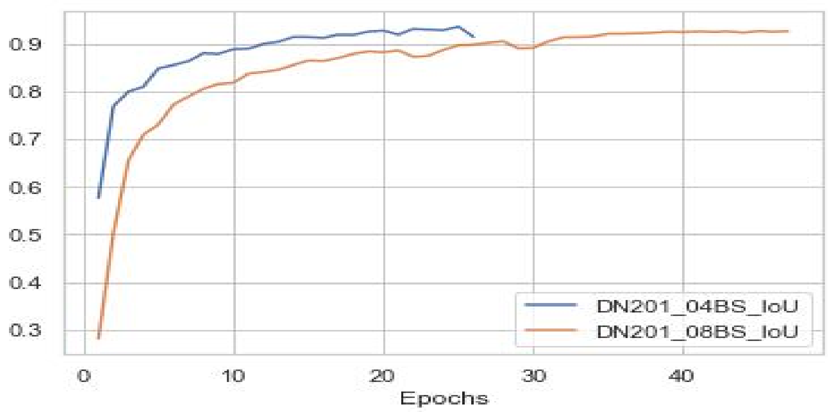


Fig. 7 (b). DenseNet201as encoder UNET Model graph between epochs and IoU values

Fig. 7 (b) depicts the performance between DenseNet201 as encoder UNET Model with a batch size of 4 images and DensetNet201 as encoder UNET Model with a batch size of 8 images. DenseNet201 as encoder UNET Model with a batch size of 04 images is given a better performance. Therefore, DenseNet201 as encoder UNET Model with a batch size of 04 images has been selected for this work.

(a) Model Training

Deep learning models are trained with a training set of images of the dataset. During the training phase, the Class Categorical Cross Entropy is an optimized loss function that should be optimized with minimum value. Image segmentation metrics such as Intersection over Union (IoU) values and Dice Coefficients value are optimized with maximum value. Fig. 8 (a) represents the graph during training of UNET Model as baseline model and Fig. 8 (b) depicts the graph of training of the DenseNer201 as encoder UNET better result giving model.

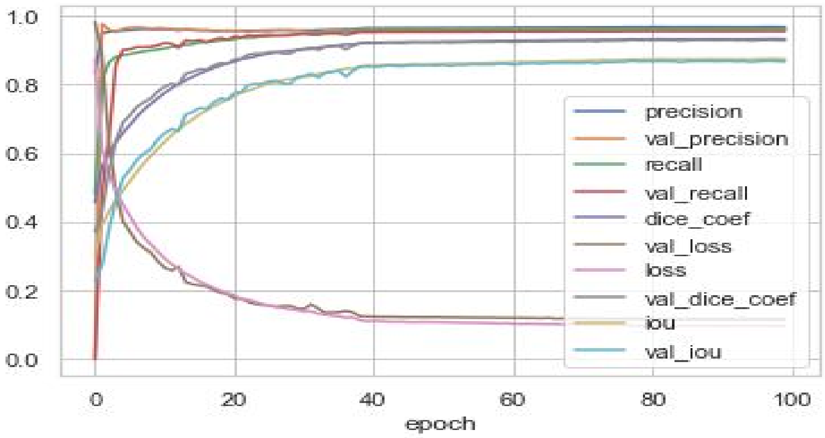


Fig. 8 (a). UNET Model Training Graph

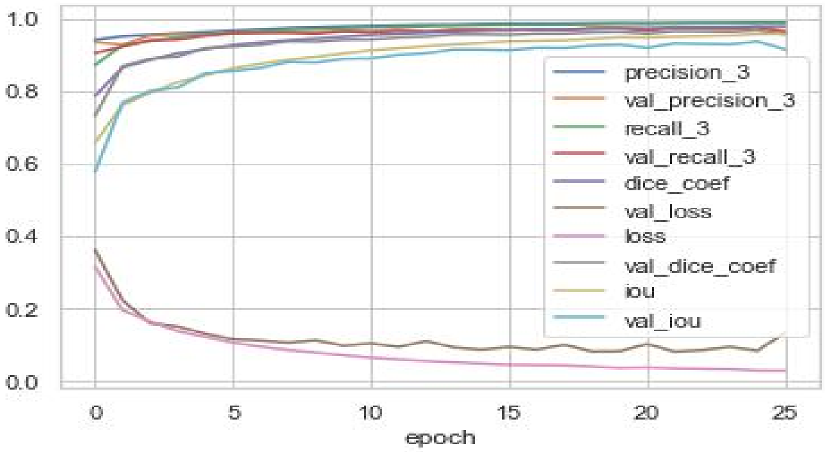


Fig. 8 (b). DenseNet201 as encoder UNET Model

The deep learning models were trained for 100 epochs on COVID-19 Segmentation dataset. Best models were save, if and only if the loss function become minimum. The ReduceLRonPlateau method of callback with parameters 1-e6 minimum learning rate, reduce factor 0.1 and patience 04 epochs has been selected to maintain the appropriate learning rate during model training. The early stopping techniques were also used after patience 20 epochs to prevent the overfitting of deep learning segmentation models. The Categorical Cross-Entropy function was used as loss funtions.

IV. RESULTS AND DISCUSSIONS

The validation process is running during the training phase, after each epoch of training, one run of validation is also executed on the validation set of images. The calculation of the validation IoU and validation Dice Coefficient is being calculated for the DenseNet169 as encoder UNET Model, DenseNet201 as encoder UNET Model, MobileNet [16] as encoder UNET Model and UNET (Baseline Model). The performance clearly shows that DenseNet169 as encoder UNET Model and DenceNet201 are given better results in terms of higher validation IoU and validation Dice Coefficient in Fig. 9(a). Fig. 9(b) shows the validation Dice Coefficient of versus epoch results on the validation set of images.

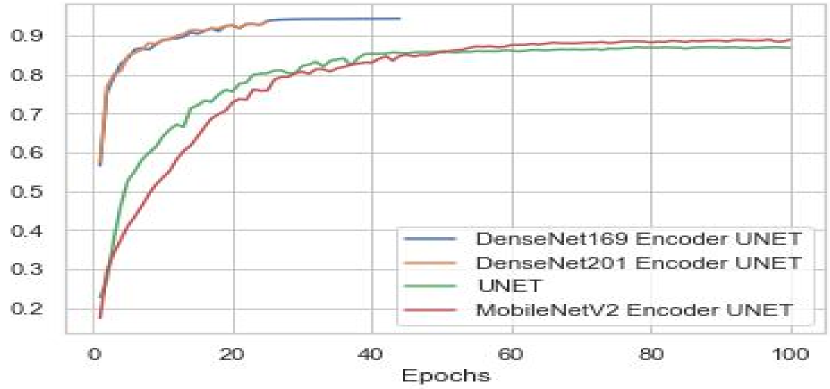


Fig. 9(a). Dice Coefficient versus epochs

The performance depicts in fig. 9(b), the Dice Coefficient of the DenseNet169 as encoder UNET Model and DenseNet201 as encoders UNET Model shows better performance than MobileNet as encoder UNET Model. After the training and validation process, the test and evaluation of Deep learning models are performed on the test set. The predicted masks (Ground Truth images) corresponding to the given input CT Scan image were predicted by various models. Table 2 depicts the results of various models predicted over the test set. In Table 2, the first column contains the input COVID-19 CT Scan Images, The second column has the Ground Truth images corresponding to the input CT Scan images, the three-column has predicted Infection Mask images by the UNET Model (Baseline Model), the Fourth Column contains the predicted infection mask images by the MobileNet as encoder UNET Model corresponding to input COVID-19 CT Scan images.

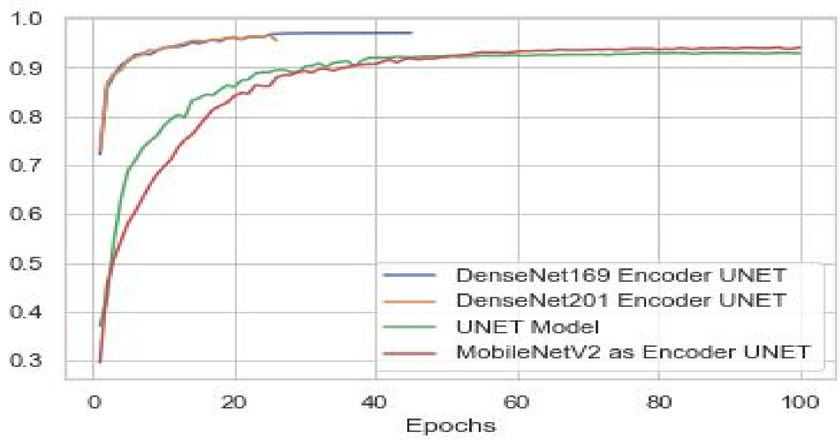


Fig. 9 (b). IoU versus epochs

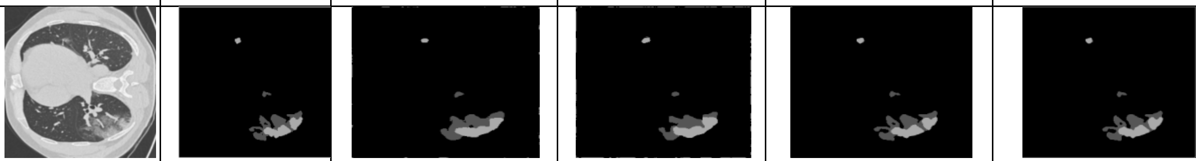
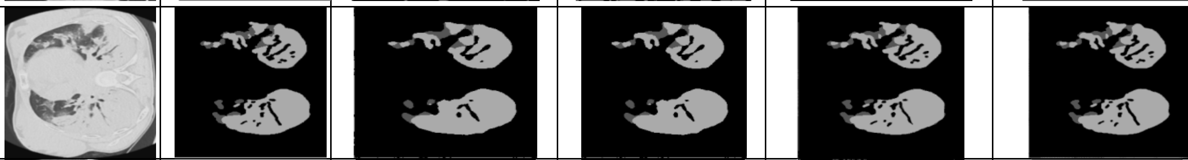
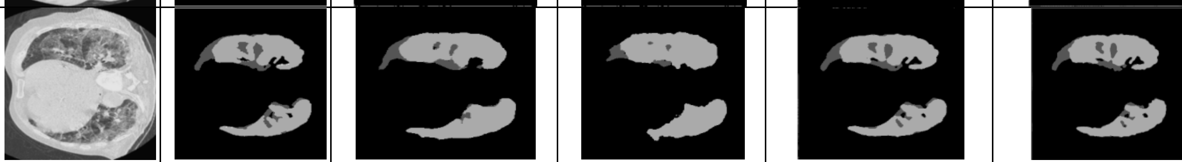
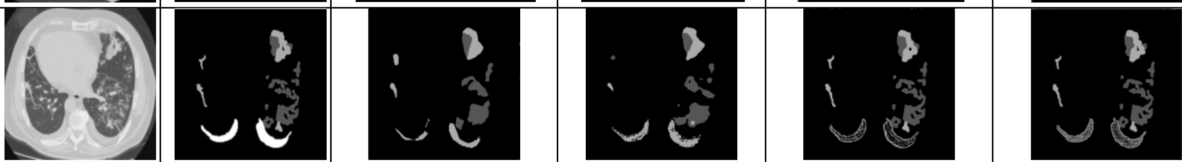
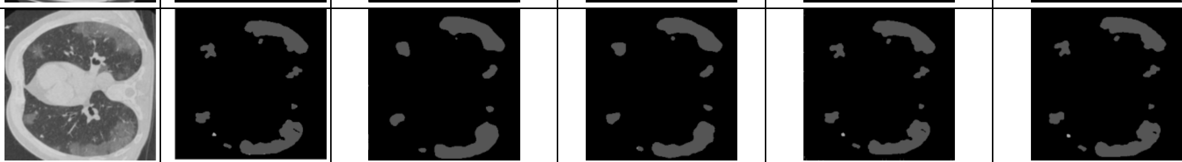
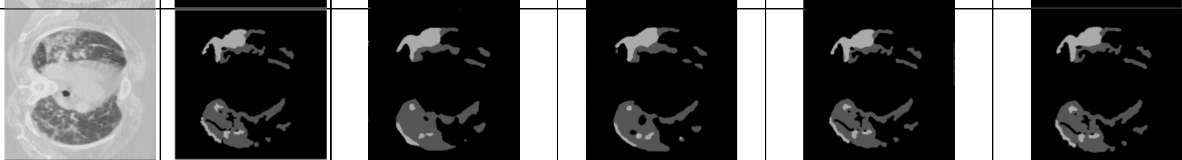
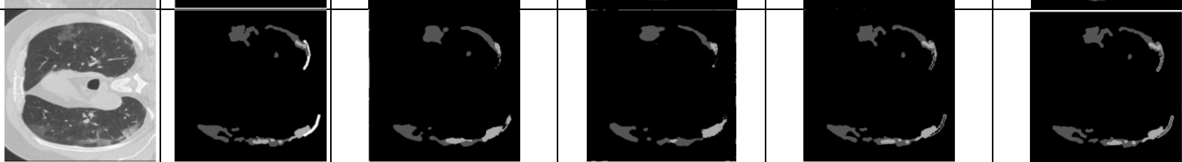
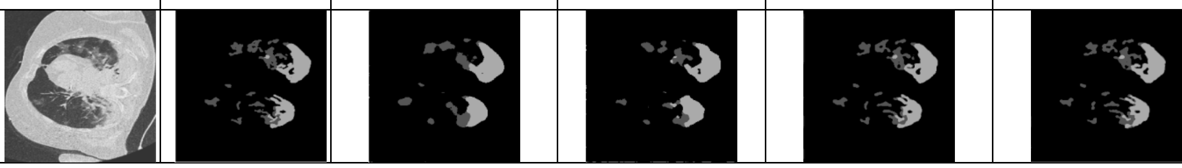
The fifth column has predicted infection mask images by the DenseNet201 as encoder UNET Model and the last column contains the predicted infection mask images by the DenseNet169 as encoder UNET Model. The Intersection over Union (IoU) value of the UNET Model (baseline model) has been achieved 86.94 and the Dice coefficient has been recorded 95.73. The improvement in metrics of segmentation models have been achieved using MobileNet as encoder UNET Model. The IoU value and Dice coefficient values are 88.90, 94.11 respectively in MobileNet as encoder UNET Model. The IoU values 93.56 and Dice coefficient value 96.64 are achieved using DenseNet201 as encoder UNET Model. The IoU value 94.34 and Dice Coefficient value 97.06 are the best model DenseNet169 as encoder UNET Model among the selected models for this work.

The DenseNet201 as encoder UNET Model and DenseNet169 as encoder UNET Model have been predicted very similar visually identical to the Ground Truth images of given COVID-19 CT Scan images of patients. Whilst, the MobileNet as encoder UNET Model and UNET Model (baseline model) have been predicted the Ground Truth images with some error. The Ground Truth images, which were predicted by the MobileNet as encoder UNET Model and UNET Model visually not identical to the real Ground Truth image of the given COVID-19 CT Scan images.

The DenseNet201 and DenseNet169 are the pre-trained models, which were trained on ImageNet dataset. The DenseNet201 model and the DenseNet169 model have 201 layers, 169 layers respectively. Whilst, MobileNet and UNET Models have less numbers of layers with compare to the DenseNet201 and DenseNet169 Models.

International Research Journal of Computer Science (IRJCS) ISSN: 2393-9842
Issue 07, Volume 08 (August 2021) https://www.irjcs.com/archives

TABLE 2- RESULTS OF VARIOUS DEEP LEARNING MODELS ON TEST SET

S. No.	Input Image	Ground Truth	UNET (Baseline model) IoU - 86.94 Dice Coef. - 95.73	MobileNetV2 – Encoder-UNET IoU - 88.90 Dice Coef.- 94.11	DenseNet201- Encoder-UNET IoU - 93.56 Dice Coef. - 96.64	DenseNet169- Encoder-UNET IoU - 94.34 Dice Coef. - 97.06
01						
02						
03						
04						
05						
06						
07						
08						
09						
10						

V. CONCLUSIONS

The COVID-19 CT Scan image segmentation performance has been improved using the transfer learning technique. The segmentation result has been improved from IoU value 86.94 in the UNET segmentation model, to 88.90, 93.56 and 94.34 using MobileNet, DenseNet201, DenseNet169 as an encoder in UNET Model respectively. The Dice coefficient has also been improved from 95.73 to 96.64, 97.06 using DenseNet201, DenseNet169 as an encoder in UNET Model. The DenseNet201 as encoder UNET Model observed as better model followed by DenseNet169 as encoder UNET Model

REFERENCES

1. J. F. Chan et al., "A familial cluster of pneumonia associated with the 2019 novel coronavirus indicating person-to-person transmission: a study of a family cluster," Lancet, vol. 395, no. 10223, pp. 514-523, Feb 15 2020, https://doi://10.1016/S0140-6736(20)30154-9.
2. N. Zhu et al., "A Novel Coronavirus from Patients with Pneumonia in China, 2019," New England Journal of Medicine, vol. 382, no. 8, pp. 727-733, 2020, https://doi:/10.1056/NEJMoa2001017.
3. Worldometer.info/ Website, access on July 22, 2021. [Online] Available: https://www.worldometers.info/coronavirus
4. Purva Asrani, Mathew Suji Eapen, Md Imtaiyaz Hassan, Sukhwinder Singh Soha. Implications of the second wave of COVID-19 in India. Lancet Respir Med 202.. June 30, 2021. https://doi.org/10.1016/ S2213-2600(21)00312-X.
5. reuters.com website, Krishna N Das and Ankur Banerjee, India's COVID death rate hit record in June after call for better data, access on July 23, 2021 [Online]. Available: https://reuters.com/world/indias-covid-death-rate-hit-record-june-after-calls-better-data-20221-07-06/
6. theprint.in Website, Abantika Ghosh and Shipra Kapoor, Daily COVID tracker latest India coronavirus numbers, access on July 25, 2021, [Online]. Available: https://theprint.in/health/daily-covid-tracker-latest-india-coronavirus-numbers-21-july/465534/
7. firstpost.in Website, What is R-number, why you should know about it, and what it says about COVID-19 situation in India, access on July 25, 2021, [Online]. Available: https://www.firstpost.com/india/what-is-r-number-why-you-should-know-about-it-and-what-it-says-about-covid-19-situation-in-india-9807131.html.
8. The COVID-19 segmentation dataset, access on May 22, 2021, [Online]. Available https://medicalsegmentation.com/covid19/.
9. The Slicer Software 4.11, downloaded on May 23, 2021, [Online]. Available https://www.slicer.org
10. Tensorflow Libray, downloaded on June 02, 2021, [Online]. Available https://www.tensorflow.org/
11. Keras Libray, downloaded on June 02, 2021, [Online]. Available https://www.keras.io/
12. Albumentations library, downloaded on June 03, 2021, [Online]. Available https://albumentations.ai/
13. Ronneberger O, Fischer P, Brox T.,"U-Net: convolutional networks for biomedical image segmentation." In: Lecture Notes in Computer Science. Springer, Berlin; 2015. p. 234– 41.
14. Google Colab, accessed in June-July, 2021, [Online]. Available https://colab.research.google.com/notebooks/Intro.ipynb?utm_source=scs-index
15. Gao Huang and Zhuang Liu and Laurens van der Maaten and Kilian Q. Weinberger, "Densely Connected Convolutional Networks", arXiv 1608.06993, 2016
16. G. Howard, M. Zhu, B. Chen, D. Kalenichenko, W. Wang, T. Weyand,M. Andreetto, and H. Adam, ''Mobilenets: Efficient convolutional neural networks for mobile vision applications,'' Apr. 2017

