Fully Convolutional Network and UNet for Lung Segmentation

[1]Humera Shaziya, [2] Prof Shyamala Kattula

[1]Reearch Scholar, [2]Professor
[1]Department of CSE, UCE
[1]Osmania University, Hyderabad, India

Abstract—Lung segmentation has been an active area of research to study the methods on effective segregation of lungs parenchyma. When the thoracic CT image is focused to investigate the lung conditions, there is no need to process the adjacent tissues of lungs. Therefore lung region can be extracted from the CT image and can provide as input to subsequent operations. Apparently lung segmentation can be considered as the prerequisite step to examine whether there are any lung nodules that can be benign or malignant. Several methods have been proposed. Conventional techniques deal with the pixel values and perform operations on those values. However the recent developments in the area of machine learning and deep learning have remarkable impact on the accuracy of separating the image into distinctive parts. The proposed work has presented two deep learning models for effectively segmenting the lung fields. The first one is fully convolutional network (FCN) and the second one is UNet. The FCN model has achieved the dice coefficient of 78.17% and UNet resulted in 98.13% dice coefficient. Therefore UNet has been an appropriate model for segmentation and showed better results compared to FCN.

***Index Terms*—Lung Segmentation, Deep Learning, Fully Convolutional Network, UNet**

I. INTRODUCTION

Lung segmentation is a significant task to perform for several applications. When thoracic computed tomography (CT) scan is taken and is given as input to any automated system for the purpose of diagnosis of any lung condition including cancer. It process the entire image that could over burden the processing system. Instead lung parenchyma is separated from the surrounding tissues apparently it would result in computationally efficient processing of lung regions. Deep learning structures have been quite successful in doing automatic diagnosis of medical conditions through images. Convolutional neural network (CNN) is used for working with images. CNN is primarily utilized for image classification while Fully Convolutional Network (FCN) is better suited for image segmentation. Therefore FCN has been developed for the purpose of lung image segmentation.

UNet is another model for performing image segmentation. It's structure is different from FCN and it segments the region of interest efficiently and accurately. UNet comprises of two paths shrinking and expanding to work with images to segment by retaining the important features of the images. Figure 1 presents the general fully convolutional network architecture. As it is shown, there are blocks of convolutional layers followed by maxpool and ends with dense layer which is similar to convolutional neural networks. However the last dense layer has been replaced by the convolutional layer that upsamples the image data.

The original UNet architecture has the form shown in figure 2. It comprises of four block of two convolutional layers, each block is followed by the maxpool layer in the contracting path. Subsequently there're two convolutional layers that lead to expansions path. Similar to contracting path, expansion path consists of four blocks of two convolutional layers and a maxpool layer.

To address the challenge of working with handling of insufficient data has been handled through the concept of data augmentation. For every image 8 different versions are generated through shift and rotation operations. Network architecture has been developed and hyperparameters have been tuned which is elaborated in further sections.

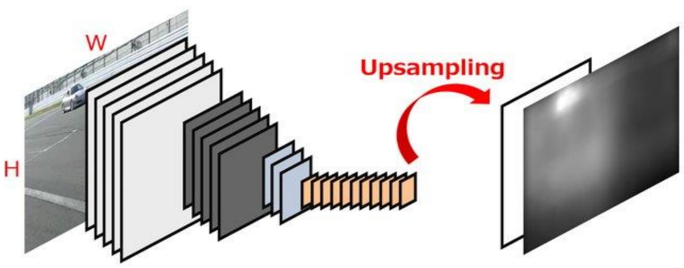

Fig 1 FCN Structure

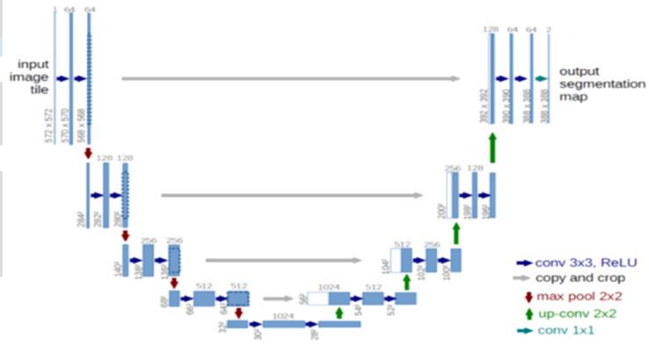

Fig 2 UNet Structure

II. RELATED WORK

Lung segmentation has been studied thoroughly for various applications. One of them being segmenting the lungs region to detect the lung nodules and classify into benign and malignant types. The problem has been addressed since the time of basic image processing capabilities wherein the threshold value is leveraged to delineate into two or more distinct segments. These types of methods are known as conventional methods. With the advent of machine learning methods, experts used to identify the features and later feed into the model so that the machine learning model can classify it into classes. Furthermore deep learning has revolutionized the way features are extracted from images. It can first learn the features from the images and subsequently perform the classification. Therefore it has now integrated both the tasks into a single structure called as convolutional neural networks (CNNs). Paper [1] presented a deep learning approach for the segmentation of lungs. The methods employed are convolutional neural networks based on encoder and decoder logic. The minimum and maximum dice score achieved is 92% and 97% respectively. The average dice score is 96%. The work [2] demonstrates lung segmentation methods through progressive holistically nested networks on 929 CT scans out of which 848 are publically available. Dice score achieved is 98%. Authors in [3] proposed a UNet architecture. The contracting and expanding path consists of two 3x3 convolutions and a relu activation functions. The dice coefficient achieved is 95%. Paper [4] discusses the development of deep convolutional neural networks. UNet and VNet models have been implemented for the purpose lung segmentation. The models were evaluated using dice and Jaccard, coefficient, Hausdorff distance, nodule coverage area. UNet achieved 98%, 96%, 85% dice, Jaccard and coverage values respectively and Hausdorff distance of 3.9. While VNet achieved 97%, 95%, 52% dice, Jaccard and coverage values respectively and Hausdorff distance of 4.4. The work done in [5] performed lung segmentation on high resolution computed tomography. The hand crafted features and deep features are combined to generate the feature map for the detection of lung area. The dice score is 89%. Paper [6] developed residual UNet model. Feature extraction has been carried out automatically through UNet model. Experiments were conducted on 3 datasets Luna16, Vessel12 and Hug-ILD and achieved dice coefficient of 98.6%, 99.6% and 98.6% respectively. The authors in [7] developed 2 UNet and ENet models for lung segmentation. The dataset experimented comprises of 42 studies. ENet achieved dice score of 95.9% and executed in 20.32 sec. The work carried out in [8] performed lung segmentation using generative adversarial network (LGAN). The experiments are conducted on 2 datasets lung imaging dataset consortium (LIDC) and quantitative imaging network (QIN). Evaluation has been performed using segmentation quality and shape similarity. The paper [9] proposed the amalgamation of manual feature extraction using morphological operations and giving those as input to modified UNet model for lung segmentation. The resulting dice score is 97.31%.

III. DEEP LEARNING MODELS FOR LUNG SEGMENTATION- FCN AND UNET

FCN Architecture: FCN comprises of convolutional layers, activation function, maxpool, flatten and dense layers and an upsampling. The proposed FCN architecture has got 2 convolutional layers, each followed by a non-linear activation function, relu and max pool operation whose size is 2x2. As in a normal convolutional neural network, FCN also employs convolutional layers for the extraction of features from the image. The activation function of FCN model is relu whose output values could be 0 or parameter itself depending on whether its parameter is negative or positive. To reduce the computational overhead, the dimension of the image is reduced using downsampling method through max pooling method. Dense layers are also incorporated in the architecture to vectorize the learned values. The final layer of FCN is the convolutional layer and upsampling which is leveraged to output the result of the model in the form of an image. Figure 3 shows the architecture of the FCN model.

The FCN architecture shown in figure 3 comprises of an input layer two convolutional layers together then a maxpool, subsequently there's a dense layer and a convolutional layer that occurs twice finally the result is upsampled to generate a segmented lungs image. The figure also shows the number of filters specified for every layer right under the layer name. The values for filter size, activation function employed and padding are presented in the same figure. The proposed work provides 186 images and their corresponding masks as input to the FCN model as training data and 81 as validation data. Image size is 128x128 and each image is preprocessed and normalized. The entire dataset is divided into training and testing sets. Figure 4 presents the details on the layer name, number of filters in each layer, size of each filter and image dimensions. The process of training begins with image size of 128x128. Furthermore the max pool layer makes it half i.e 64x64 and later the upsampling layer scale it up to 128x128 As mentioned earlier, the FCN model developed accepts a total of 267 images of the lung CT images and their masks.

The dataset is basically divided into training and testing in 90% and 10% respectively. Further the 90% training set is divided into 70% training samples and remaining 20% validation samples. There are four convolutional layers having 16, 32, 64, 1 filters for layer 1,2,3,4 respectively. Fully connected also known as dense layers are two and have 64 nodes in each. Adam optimization algorithm has been harnessed and yields a binary crossentropy loss value. The model is trained for 50, 100, 150 and 200 epochs to examine the outputs of the model for various epochs.

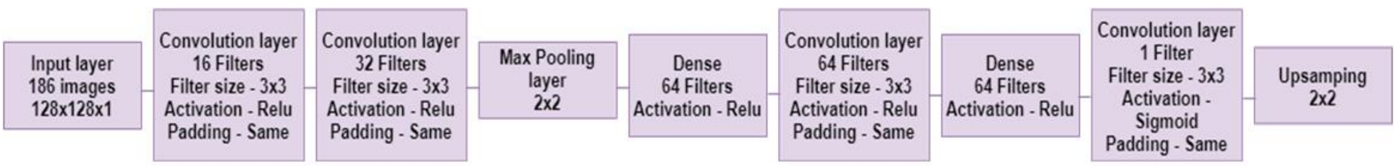

Fig 3 Proposed FCN Architecture

Layer	Filters	Filter/ pool size	Image Dimensions
Input	-	-	128x128
Con1	16	3x3	128x128
Con2	32	3x3	128x128
MP1	-	2x2	64x64
Dense	64	-	64x64
Con3	64	3x3	64x64
Dense	64	-	64x64
Con4	64	3x3	64x64
Up1	-	2x2	128x128

Fig 4 FCN Configuration

UNet Architecture: UNet another deep learning model has been used for the purpose of segmentation rather than classification because the structure of UNet is designed in such a manner that the output is an image and not just the classes to which the image belongs. The structure has been developed in a manner that looks like a u shaped symbol therefore it has been named as UNet. Similar to FCN, UNet also extract features from the images and downsample it while moving from upwards to downwards path. At a point it stops moving down and starts to upsample the image to bring the important features that has been lost at downsampling phase. When it is going in upwards direction it concatenate the image features from the corresponding downwards path components. This way the segmented output image is constructed and given as the output. Figure 5 presents the proposed UNet architecture.

Table 6 shows the configuration of the proposed UNet model. Since there are two paths in UNet downwards and upwards paths, convolutional layers are present at both the sides. There are 4 convolutional layers at each side. There is a concatenation operation performed at the corresponding layers in both the paths. The figure shows one layer is concatenated with the succeeding layer in the downwards path whereas the concatenation is done with succeeding layer as well as corresponding layers in the upwards path. The hyperparameters chosen for UNet model are 0.001 learning rate, 50% dropout rate and adam
optimizer. The model is trained for 50, 100, 150, 200 epochs.

Training: The training process begins by defining the model and then invoking fitgenerator method. The dataset is divided into batches. A batch is a set or group of data elements. A batch size denotes the total number of training elements in a particular batch. An optimization algorithm is used to iterate the training examples number of times to find the optimum results. Optimization algorithm used in this study is adam. FCN and UNet are trained using adam. Adam is a variant of stochastic gradient descent algorithm. Optimization algorithms operate in forward and backward manner. An epoch is one such pass of the entire dataset.

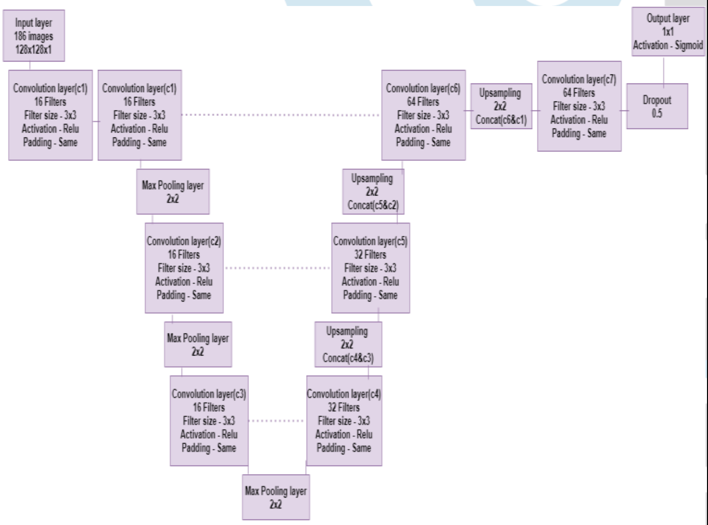

Fig 5 UNet Architecture

Layer	Filters	Filter/pool size	Image Dimensions	Concat
Input	-	-	128x128	-
Con1	16	3x3	128x128	Input
Con1	16	3x3	128x128	Con1
MP1	-	2x2	64x64	Con1
Con2	16	3x3	64x64	MP1
MP2	-	2x2	32x32	Con2
Con3	16	3x3	32x32	MP2
MP3	-	2x2	16x16	Con3
Con4	32	3x3	16x16	MP3
Up1	-	2x2	32x32	Con4 &Con3
Con5	32	3x3	32x32	Up1
Up2	-	2x2	64x64	Con5 &Con2
Con6	64	3x3	64x64	Up2
Up3	-	2x2	128x128	Con6 &Con1
Con7	64	3x3	128x128	Up3

Fig 6 UNet for Lung Segmentation

Dataset: The dataset [10] has been employed for the purpose of lung segmentation. There are 267 images and their corresponding ground truth. The dimension of each image is 128 x 128.
and the preprocessing operation minimizes the dimensions of each image to 32 x 32 pixels. The preprocessing is done so that the processing power required can be reduced. Each image is normalized after resizing. Figure 7 (left) shows one CT sample image and figure 7 (right) presents its corresponding segmentation map with the ground truth.

Data Augmentation: Dataset having more samples would give better results. Therefore in order to increase the number of images data augmentation techniques have been applied. The proposed model has selected rotation operation to augment the data. There are 8 different images based on rotation operation is generated and given to the model.
Figure 8 shows generated eight images through rotation operation.

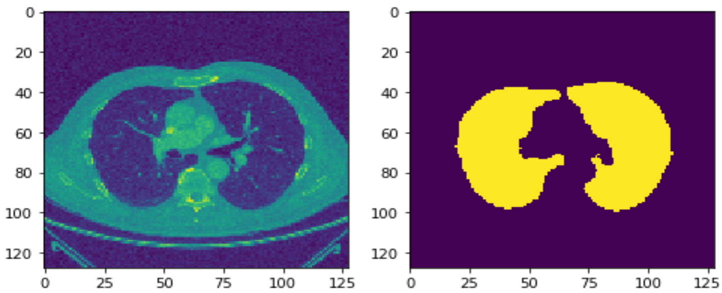

Fig 7 (Left) CT sample image (Right) Ground truth

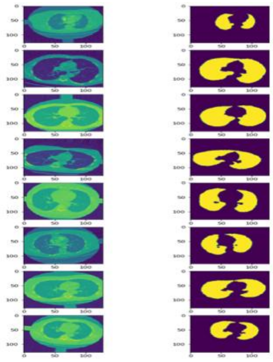

Fig 8 Data Augmentation

IV. WORKING OF THE MODELS

The experiments that have been conducted on the developed model for epochs 50, 100, 150 and 200. Figure 9 shows the investigations done for data augmentation of 4 images, 8, 16 and 32 images and also without data augmentation. It is evident from the results that no augmentation achieves good values during training however during validations augmentation generates better results.

Figure 11 presents the not so good quality lung segmented image. The quality shows that it not only segments the lungs but also the adjacent tissues. Figure 12 is the output of model which is better than the other segmented images produced by the model. It demonstrates that FCN is not producing good results for segmentation.

The experiments that have been conducted on the developed model for epochs 50, 100, 150 and 200. Figure 10 shows the investigations done for data augmentation of 4 images, 8, 16 and 32 images and also without data augmentation. It is evident from the results that no augmentation achieves good values during training however during validations augmentation generates better results.

Figure 13 presents the not so good quality lung segmented image. However that itself is an acceptable quality. It demonstrates how good UNet model is for the purpose of segmentation. Figure 14 is the output of model which is better than the other segmented images produced by the model.

DA	Epoch	Loss	DC	IOU	Acc	Val_Loss	Val_DC	Val_IOU	Val_Acc	Quality
4	50(48)	0.322	0.556	0.4996	0.8368	0.3389	0.5081	0.5453	0.8412	Bad
4	100(99)	0.2387	0.6333	0.579	0.8665	0.2864	0.6507	0.6056	0.8649	Bad
4	150(144)	0.1961	0.7421	0.7327	0.9026	0.2205	0.7033	0.6587	0.9029	Bad
4	200(197)	0.1669	0.7512	0.7418	0.914	0.2249	0.7283	0.6862	0.9035	Better
8	50(48)	0.2533	0.6361	0.6317	0.877	0.257	0.641	0.6459	0.8958	Bad
8	100(93)	0.2171	0.732	0.6939	0.8903	0.2538	0.698	0.6634	0.8928	Bad
8	150(146)	0.1777	0.7756	0.7481	0.9093	0.1824	0.7568	0.7251	0.9252	Bad
8	200(197)	0.1712	0.7884	0.7663	0.9127	0.1808	0.7702	**0.7321**	0.926	Bad
16	50(48)	0.2501	0.6687	0.6461	0.8799	0.3787	0.6216	0.5402	0.8156	Bad
16	100(98)	0.1988	0.7409	0.7118	0.9001	0.2418	0.7148	0.6668	0.8967	Ok
16	150(150)	0.1671	0.7781	0.7542	0.9128	0.247	0.7343	0.6593	0.8889	Ok
16	200(199)	0.1562	0.7889	0.7645	0.9173	0.1997	0.7423	0.7002	0.9205	Bad
32	50(50)	0.215	0.7198	0.6942	0.8938	0.2739	0.7016	0.6312	0.875	Bad
32	100(96)	0.182	0.7622	0.7357	0.9067	0.2102	0.7277	0.693	0.9133	Better
32	150(150)	0.1534	0.7997	0.7702	0.9181	0.2485	0.7542	0.6672	0.8914	Bad
32	200(199)	**0.1487**	**0.8017**	**0.7731**	**0.9204**	0.1838	**0.7817**	0.7212	**0.9254**	ok
NoDA	200(200)	0.1655	0.7876	0.7489	0.9327	**0.1184**	0.7724	0.7219	0.9222	Better

Fig 9 FCN Results for DA, Loss, DC, IoU, Acc, Quality

DA	Epoch	Loss	DC	IOU	Acc	Val_Loss	Val_DC	Val_IOU	Val_Acc	Quality
4	50(50)	0.0866	0.8895	0.8808	0.9547	0.0624	0.9259	0.9198	0.9801	Vgood
4	100(93)	0.0621	0.9257	0.918	0.9575	0.442	0.9431	0.9294	0.9832	Vgood
4	150(124)	0.0461	0.9452	0.9383	0.9629	0.0326	0.959	0.9515	0.9881	Notgood
4	200(190)	0.0389	0.9466	0.9473	0.964	0.0875	0.9466	0.9315	0.9817	Fair
8	50(50)	0.0698	0.9148	0.9034	0.9565	0.07	0.9351	0.918	0.9795	Good
8	100(98)	0.0399	0.9469	0.9441	0.9629	0.0823	0.9434	0.9273	0.9818	Vgood
8	150(128)	0.0567	0.9346	0.9303	0.9603	0.0498	0.947	0.9344	0.9835	Vgood
8	200(183)	0.0413	0.9394	0.9508	0.9634	0.0591	0.95	0.9418	0.9862	Fair
16	50(49)	0.0532	0.937	0.9289	0.9602	0.0839	0.936	0.9162	0.9795	Notgood
16	100(94)	0.0542	0.9316	0.933	0.9607	0.0322	0.9589	0.9523	0.9883	Good
16	150(143)	0.056	0.9426	0.9382	0.9607	0.28	0.9599	0.9611	0.9903	Vgood
16	200(151)	0.0288	0.9626	0.9486	0.9661	0.0992	0.9543	0.9428	0.9848	Vgood
32	50(49)	0.0691	0.9199	0.9172	0.957	0.0509	0.9387	0.9356	0.9848	Good
32	100(99)	0.0497	0.9388	0.9398	0.9618	0.0395	0.955	0.9485	0.987	Notgood
32	150(147)	0.0481	0.9469	0.9447	0.9617	0.0407	0.9477	0.9476	0.9874	Notgood
32	200(184)	0.0366	0.9634	0.9403	0.9603	0.0187	0.9813	0.9639	0.9916	Good
NoDA	**200(185)**	**0.0261**	**0.9719**	**0.961**	**0.9906**	**0.991**	**0.9477**	**0.9266**	**0.982**	**Vgood**

Fig 10 FCN Results for DA, Loss, DC, IoU, Acc, Quality

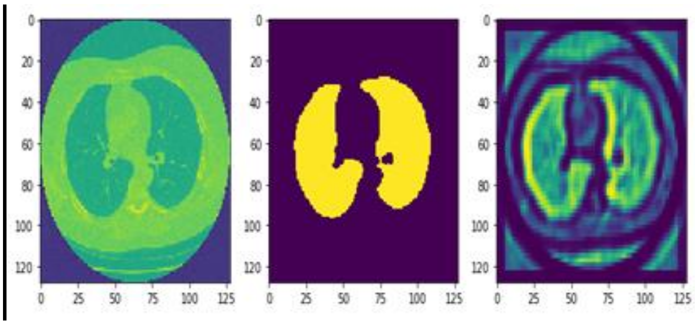

Fig 11 FCN Bad Quality Results

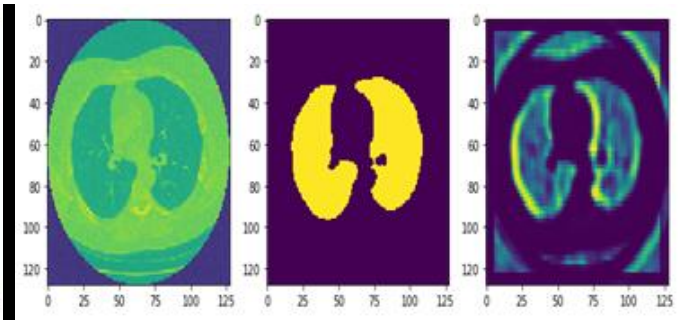

Fig 12 FCN Good Quality Results

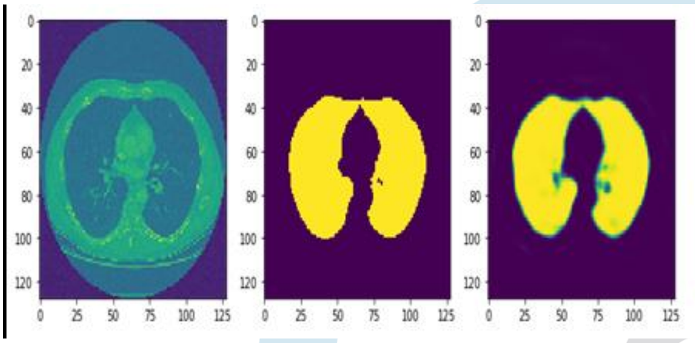

Fig 13 UNet Not So Good Results

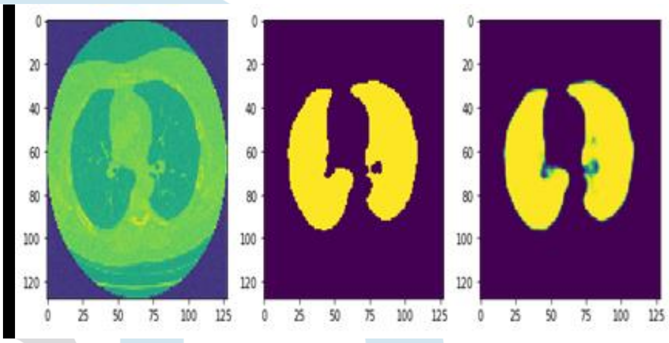

Fig 14 UNet Good Results

Both FCN and UNet models generate feature maps that include image properties like edges, shapes shown in figure 15 for FCN and figure16. Apparently the difference between FCN and UNet is whether images are upsampled or not. In FCN images are only downsampled while in UNet images are downsampled during feature learning process and further upsampled and mapped with learned feature maps.

The features identified through FCN model clearly shows that the system has generated features that are not part of the lungs area. Therefore other adjacent tissues are also classified as lungs region leading to incorrect segmentation results.

The features generated by UNet model have included only the lung fields as the region of interest. Apparently this has led to the identification of features relevant to the current problem of lungs segmentation.

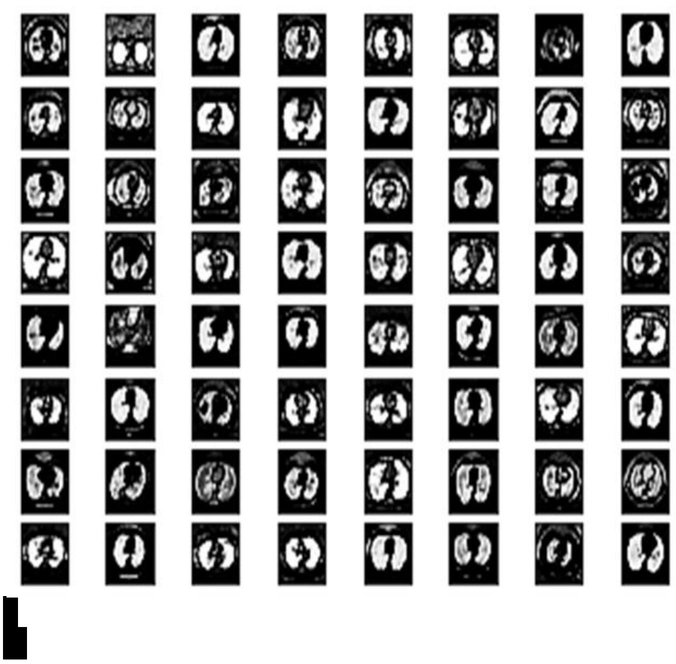

Fig 15 FCN Features Identified

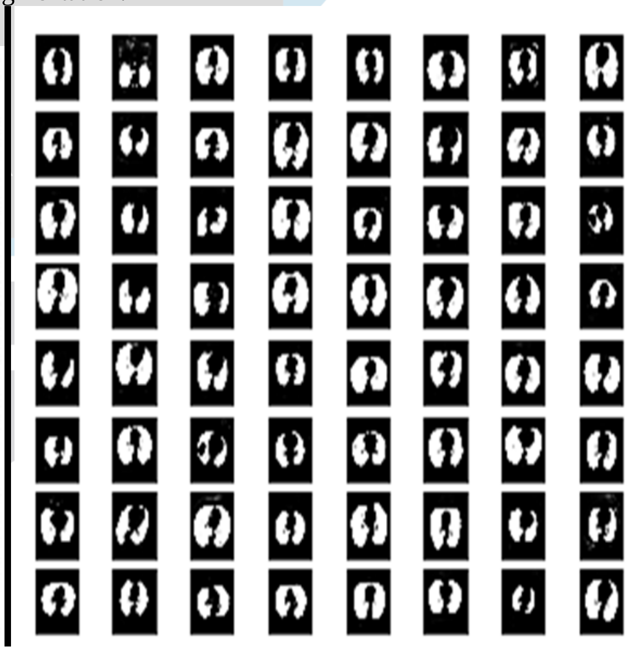

Fig 16 UNet Features Identified

Region based or boundary based methods are used as the metrics for evaluating the performance of the segmentation algorithms. Dice Coefficient is a type of region based method whereas haussdorf distance is a kind of boundary based method. The most commonly used metric is region based dice coefficient \cite{b18}. Intersection over Union (IoU) is another popular measure of performance of segmentation processes. Hence proposed UNet and proposed FCN models are evaluated through dice coefficient and IoU. Loss is measured using cross entropy. The similarity of two different sets of values is measured by dice coefficient (DC). If DC is 1, it implies that both the sets are identical and also indicate that the segmentation is accurate. Otherwise the segmentation has not been done properly. It is given by the following equation

$$Dice(A,P) = \frac{2\,||A \cap P||}{||A|| + ||P||}$$

where A is ground-truth and P is predicted values, $||A \cap P||$ is the intersection of elements and $||A||$ and $||P||$ are the cardinalities. When both the sets are identical the DC is 1.0 and 0.0 otherwise.
IoU also referred to as Jaccard Coefficient measure the overlap between actual mask and predicted output. The equation is as follows

$$IoU/Jaccard(A,P) = \frac{||A \cap P||}{||A \cup P||}$$

where A is ground-truth and P is predicted values, $||A \cap P||$ is the intersection of elements, $||A \cup P||$ is the union.When both the sets are identical the IoU is 1.0 and 0.0 otherwise.
The model learns and improves the loss which is measured through loss function. Cross-entropy (CE) loss or log-loss is defined as the measure of the performance of the classifier.
$\text{Cross Entropy} = -\sum_{i}^{z} a_i \log(p_i)$ Where z is the no of classes, a_i is the actual value and p_i is the predicted value.

V. RESULTS

FCN Results: UNet training and validation results are presented in Figure 17. Training epochs are plotted along the X axis and the outcome in the form of dice coefficient, IoU and accuracy are plotted along the y axis. The obtained dice coefficient for the training set is 0.8017, IoU is 0.7731 and accuracy 0.9204. The validation results are 0.7817, 0.7212, 0.9254 for dice coefficient, IoU, accuracy respectively. Figure 17 shows the training and validation loss. No of epochs are indicated at X axis and binary crossentropy loss is modeled at y axis. 0.1487 and 0.1838 are the values of the loss for training and validation loss .

UNet Results: UNet training and validation results are presented in Figure 18. Training epochs are plotted along the X axis and the outcome in the form of dice coefficient, IoU and accuracy are plotted along the y axis. The dice coefficient obtained for the training set is 0.9634, IoU is 0.9403 and accuracy 0.9603. The validation results are 0.9813, 0.9639, 0.9916 for dice coefficient, IoU, accuracy respectively. Figure 18 shows the training and validation loss. No of epochs are indicated at X axis and binary crossentropy loss is modeled at y axis. 0.0366 and 0.0187 are the values of the loss for training and validation loss .

Comparison: Figure 19 shows comparison of the results of proposed work with the existing literaturePaper [1] achieved 97.4% DC on 354 xray chest images. Work [2] got 98% DC on 929 CT scans. Paper [3] on LIDC dataset obtained 95.02% DC. Work [4] on 130 CT scans achieved 98.45% DC and 96.97% IoU. Paper [5] investigated the working of their model on 108 images to achieve 89.42% DC. Paper [6] examined Luna16 dataset and obtained 98.63% (mean) DC. Paper [7] performed experiments on 42 studies to achieve 95.9% (mean) DC and conducted study on ILD dataset to obtain 96.45% (average) DC. Paper [8] performed experiments to quantify both DC 98.5% (mean) and IoU 92.25% (mean), 97.15% (median) on 220 CT scans. Work [9] achieved 97.31% DC on LIDC data. The proposed UNet model outperformed most of the existing work and has achieved 98.13% DC and 96.39% IoU on 267 CT scans.

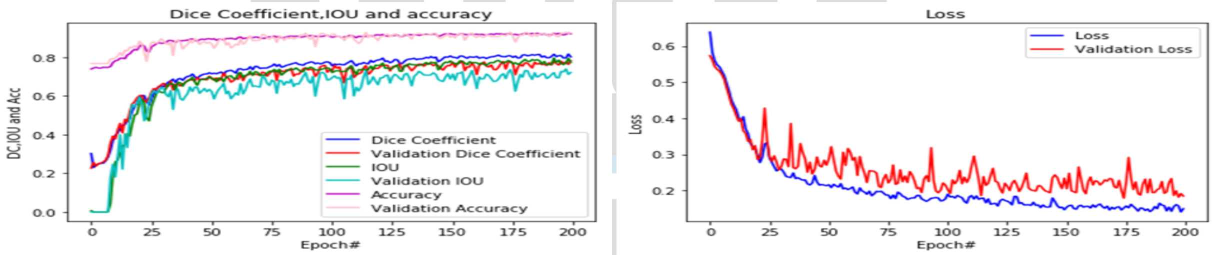

Fig 17 (Left) Graph FCN DC, IoU, Accuracy (Right) Loss

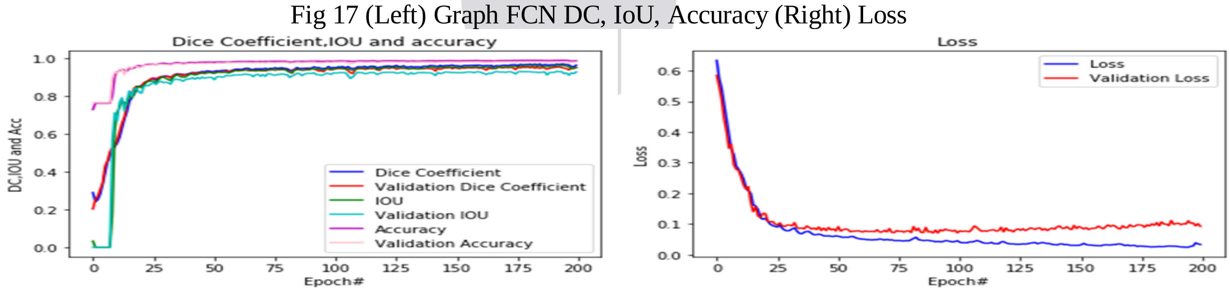

Fig 18 (Left) Graph UNet DC, IoU, Accuracy (Right) Loss

Work	Dataset	DC(%)	IoU(%)
Kalinovsky, Alexander, and Vassili Kovalev(2016)	354 Xray chest images	97.4	-
Harrison, Adam P., et al. Springer, Cham, 2017	929 CT scans	98	-
Skourt, Brahim Ait, Abdelhamid El Hassani, and Aicha Majda. *Procedia Computer Science* 127 (2018)	LIDC	95.02	-
Gu, Yuchong, et al. *2019 IEEE 16th International Symposium on Biomedical Imaging (ISBI 2019)*. IEEE	130 CT scans	98.45	96.97
Pang, Ting, et al. *BioMed research international* 2019		89.42	-
Khanna, Anita, et al. *Biocybernetics and Biomedical Engineering* 40.3 (2020)	Luna16	98.63 (Mean)	-
Comelli, Albert, et al. *Journal of Imaging* 6.11 (2020)		95.9 (Mean)	-
Liu, Caixia, et al. *Neural Processing Letters* 52.2 (2020)		96.45 (Average)	-
Tan, Jiaxing, et al. *Computerized Medical Imaging and Graphics*(2021)	220 CT scans	-	92.25 (Mean) 97.15 (Median)
Proposed Work	**267 CT scans**	**98.13**	**96.39**

Fig 19 Comparison of results with existing literature

VI. Conclusion

Lung segmentation has been thoroughly investigated because it is an essential prerequisite for several subsequent operations on lungs region. Conventional methods primarily depend on basic unit of pixel values and thresholds have been used to segregate the segments. Machine learning models performed classification of regions into different classes however required features to be given as input to the model. Deep learning performs both the tasks of feature extraction and classification and therefore it is a fascinating area of research for the purpose of lung segmentation. The proposed work has proposed two deep learning models that are fully convolutional networks and UNet. Dice coefficient (DC) is the metric to determine the performance of segmentation. FCN has achieved 78.17% DC whereas UNet scored 98.13% DC. Both the models have been trained for 50, 100, 150 and 200 epochs. UNet improved the DC by 19.96% relative to FCN.

VII. Acknowledgment

This work has been done under Visvesvaraya PhD Scheme for Electronics and IT (File Number: PhD-MLA-4(63)/2015-16) of Ministry of Electronics \& Information Technology (MeitY), Government of India. The authors would like to thank the editor and the reviewers for their helpful suggestions and valuable comments.

References

[1] Kalinovsky, Alexander, and Vassili Kovalev. "Lung image Ssgmentation using deep learning methods and convolutional neural networks." (2016).

[2] Harrison, Adam P., et al. "Progressive and multi-path holistically nested neural networks for pathological lung segmentation from CT images." *International conference on medical image computing and computer-assisted intervention*. Springer, Cham, 2017.

[3] Skourt, Brahim Ait, Abdelhamid El Hassani, and Aicha Majda. "Lung CT image segmentation using deep neural networks." *Procedia Computer Science* 127 (2018): 109-113.

[4] Gu, Yuchong, et al. "Multi-scale prediction network for lung segmentation." *2019 IEEE 16th International Symposium on Biomedical Imaging (ISBI 2019)*. IEEE, 2019.

[5] Pang, Ting, et al. "Automatic lung segmentation based on texture and deep features of HRCT images with interstitial lung disease." *BioMed research international* 2019 (2019).

[6] Khanna, Anita, et al. "A deep Residual U-Net convolutional neural network for automated lung segmentation in computed tomography images." *Biocybernetics and Biomedical Engineering* 40.3 (2020): 1314-1327.

[7] Comelli, Albert, et al. "Lung segmentation on high-resolution computerized tomography images using deep learning: a preliminary step for radiomics studies." *Journal of Imaging* 6.11 (2020): 125.

[8] Tan, Jiaxing, et al. "LGAN: Lung segmentation in CT scans using generative adversarial network." *Computerized Medical Imaging and Graphics* 87 (2021): 101817.

[9] Jalali, Yeganeh, et al. "ResBCDU-Net: a deep learning framework for lung CT image segmentation." *Sensors* 21.1 (2021): 268.

[10] Zhao, E. "Lung segmentation in CT images". (https://wiki.cancerimagingarchive.net/display/Public/LIDC-IDRI,0), (Accessed on 04/06/2021)