Lung Segmentation Using Deep Learning

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ABSTRACT

Segmentation is useful in different applications mainly it plays vital role in medical analysis. For image analysis of lungs, segmentation is an important step, thus it plays a major role in efficient image processing. Lung Segmentation helps to improve the early finding and treatments of lung infections. The performance of analysis and diagnosis of lung issues can be improved and it lessen the work of radiologists.

The U-Net architecture was introduced mainly for Image segmentation in Biomedical. This architectures are mainly consists of both encoders and decoders which is most important for image segmentation. The neural networks shows better performance when the network is initializes with weights which are pre-trained on huge dataset like ImageNet. The aim of this paper is to develop a system that performs automatic lung segmentation procedure to determine the boundaries of lobes from surrounding thoracic tissue using Deep Learning and to compare the U-Net and U-Net using VGG11 encoder pre-trained on ImageNet with the existing systems. The proposed system using the U-Net architecture and U-Net with VGG-11 encoder pre-trained on ImageNet achieved the accuracy of 97.63% and 98.28% respectively.

Keywords: *Fully convolutional networks (FCN), Convolutional neural network (CNN), Image segmentation, U-Net, Visual Geometry Group-11 (VGG-11), Chest X-ray (CXR), Refined linear unit (ReLU), Deep learning (DL), Machine learning (ML), Artificial intelligence (AI).*

1. Introduction

The objective of segmentation is to rearrange and additionally change the view of an image into something that is more significant and simpler to analyse. Segmentation is used to find boundaries and objects in images. It is considered the most fundamental clinical imaging as it extracts region of interest through automatic process. Semantic image segmentation classifies every pixel of an image with a relating class.

The actual yield is a high-resolution image in which every pixel is characterized to a specific class. Along these lines it is a pixel level image categorization. More patients tend to have an x-ray check-up at hospitals, which adds more workload to radiologists so here the process of lung segmentation is highly beneficial. Lung Segmentation helps to improve the early finding and treatments of lung infections. CNN is trained in end to end way for the segmentation of the input images in this method.

Also this helps in improving the accuracy in segmentation over some common datasets. Further improved verson of this method is called as U-Net neural network and a further improvisation has been made by replacing encoder of UNet with VGG11 encoder pretrained on Imagenet. This paper is structured as follows: The introduction is given in section 1. Section 2 presents literature survey. Algorithms were explained in section 3. In section 4, the proprosed methodology and the flow diagram is explained and the result is shown in section 5. Finally the result is given in section 6.

2. Literature Survey

[1] Hieu Thrung Huyn and Vo Nguyen Nat Ana proposes a deep learning method for segmenting the lung on large size chest X-ray image. This paper proposes a network architecture for lung segmentation using CNNs and traditional neural networks. The boundaries of lung region are not smooth as the other methods because the

network classified each pixel. [3] Mingje Xu,Souliang Qi, Yong Yueh, Yueyangh Teng, Lisheng Xuh ,Yhudong Yao ,Wei Qian 2019(Springer Paper). This method proposes a convolutional neural network (CNN) model to segment lung parenchyma. It does not work well with clusters of different size and density. [5] Cing-Sheng Chang, Jin-Fah Lin, Ming - Cing Lee, Christop Palm ,2020(Springer Paper) uses the architecture of DeepLabv3+ which is well known as state-of-art in the PASCAL VOC 2012 dataset. This work uses NLH Chest X-ray dataset and applies a neural network architecture for automatic lung region segmentation. The bilinear up sampling method may be not good enough and to gain more information, maybe more features from the inner layers should be concatenated with the low-level feature.

3. Algorithms

3.1 Deep Learning

Deep learning is a function that copies the human brains working in handling information and recognizing patterns which benefits in making decisions. It comes within the category of ML in AI. A large dataset and significant processing power is required by Deep Learning.

3.2 Fully Convolutional Networks

In order to convert image pixels into pixel classifications a fully convolution network makes use of the convolution neural network. The width and height of the intermediate layer is converted by the FCN to the input image's actual size as shown in Fig 1. FCN uses filters for learning. Given a pixel, the output will be a classified prediction of the corresponding pixel.


Fig.1. Fully Convolutional Network

4. Proposed Methodology

4.1 U-Net

The U-Net architecture is the best so far introduced for Biomedical Image segmentation. The architecture is composed of two main parts that are encoder and decoder. The encoder (compressive part) is used to extract the features in the image. The decoder (expansive part) uses transposed convolution to bring back the image to the actual size and promote segmentation. It is also called as "Fully Convolutional Neural Network" with no fully connected layers. The encoder consists of the repeated application of two 3x3 unpadded convolutions, each

followed by a rectified linear unit (ReLU) and for down sampling a 2x2 max pooling operation with stride 2. The number of feature channels are doubled at each down sampling. The encoder captures the context in the image. The decoder is the symmetric to that of the encoder and it is used to empower precise localization using transposed convolutions. This architecture is made up of 23 convolutional layers. The U-Net architecture is shown in Fig 2.
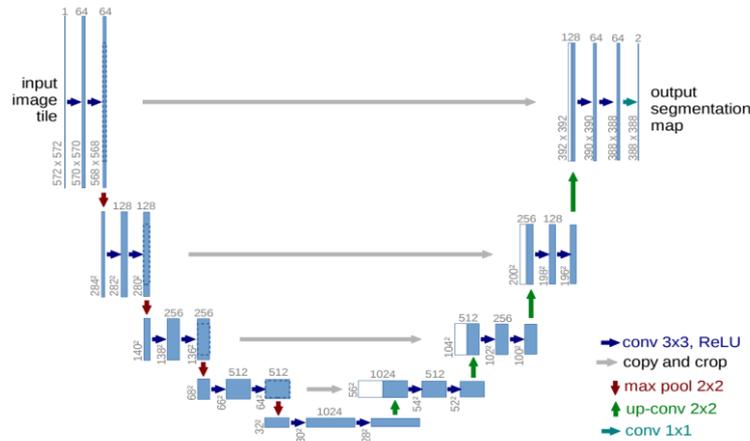

Fig.2. U-Net Architecture

4.2 VGG-11

4.2.1 VGG-11 Architecture

VGG means **Visual Geometry Group. I**t is a model which is pretrained on Imagenet, over a large dataset and contains the weights which represents the features of whichever dataset it was trained on. Using a pre-trained model saves time. This model takes input as 224 x 224 pixel image in RGB format. It uses a 3x3 convolution layer followed by 2x2 maxpooling which returns the maximum value from the pixel set.The activation function used here is the ReLU. The Softmax activation function is used for the conversion of numbers into respective probabilities. The VGG-11 architecture is shown in Fig. 3.
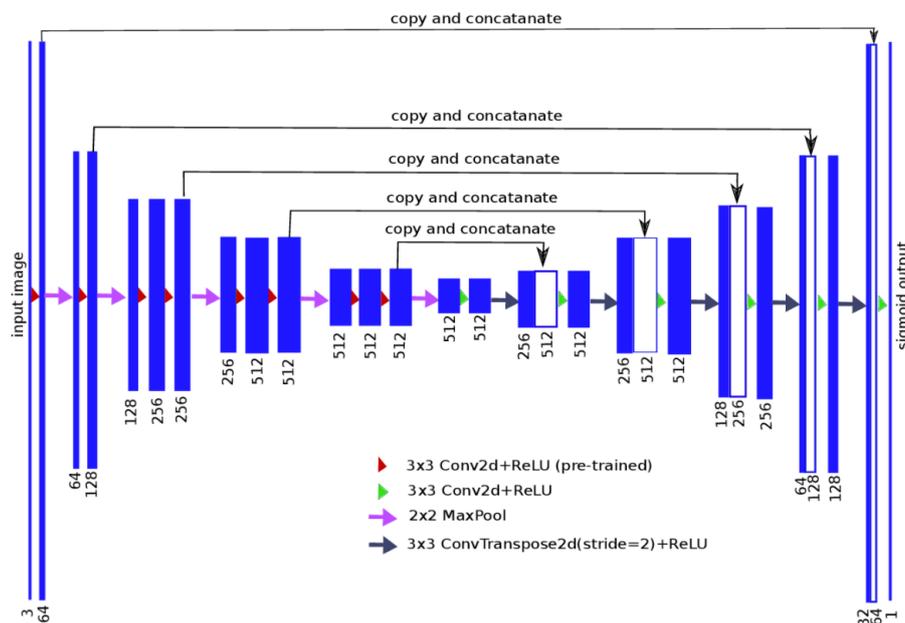

Fig.3. VGG-11 architecture

4.2.2 The VGG-11 layers

The VGG-11consists of 11 layers which is shown in Fig. 4.
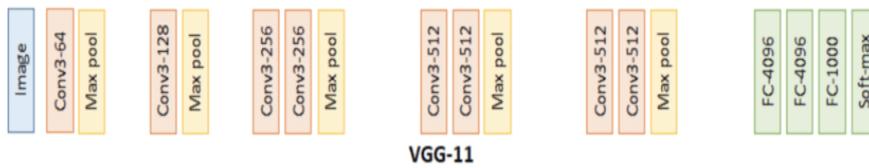
Fig.4. VGG-11 layers

4.3 Flow Diagram

The Shenzen Lung Segmentation dataset and their corresponding masks are loaded from disk. The input image is preprocessed and given as an input to build the Lung Segmentation model. The Lung Segmentation model is built and trained on the dataset using Keras and Tensorflow. The model is tested to obtain the accuracy of the Lung Segmentation model. If the obtained accuracy is greater than or equal to the estimated accuracy, the model is saved. Otherwise, the model is retrained by varying the parameters. The accuracy and loss curves are plotted using graphs. The flow diagram for building the Lung Segmentation model is shown in fig 5.
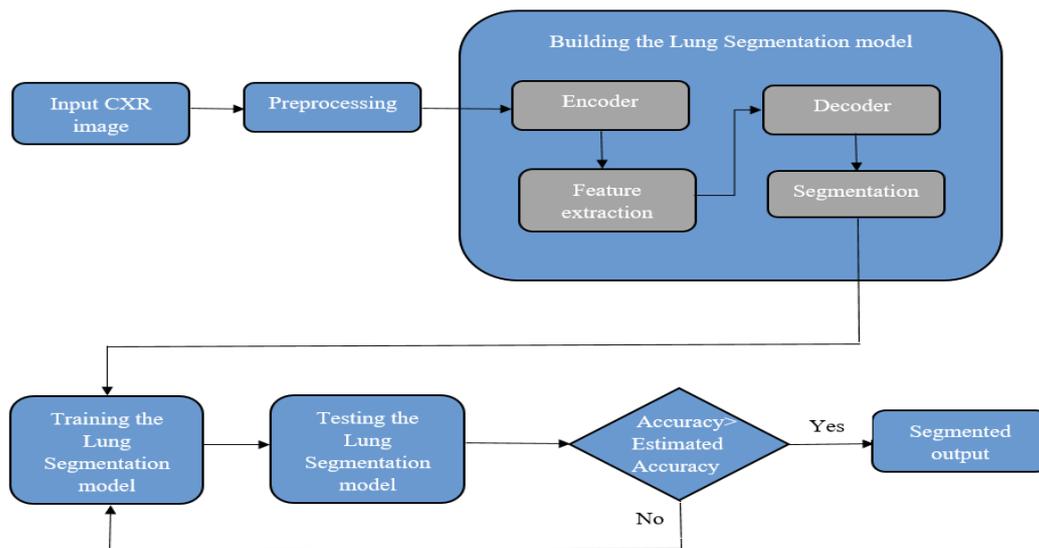
Fig.5. Flow diagram for building a Lung Segmentation model

4.3.1 Dataset

The Chest X-Ray dataset has been collected from the kaggle repository. The dataset consists of 2128 images. It consists of 1064 Chest X-Ray images and 1064 mask images as shown in Fig 6 and Fig 7.

4.3.2 Training the dataset using U-Net and VGG11 pretrained on ImageNet

The dataset is trained, and a model is developed using the U-Net - Deep learning architecture to determine the boundaries of lobes from surrounding thoracic tissue. The dataset is trained, and a model is developed using U-Net with VGG11 encoder pre trained on ImageNet- Deep learning architecture to determine the boundaries of lobes from surrounding thoracic tissue.
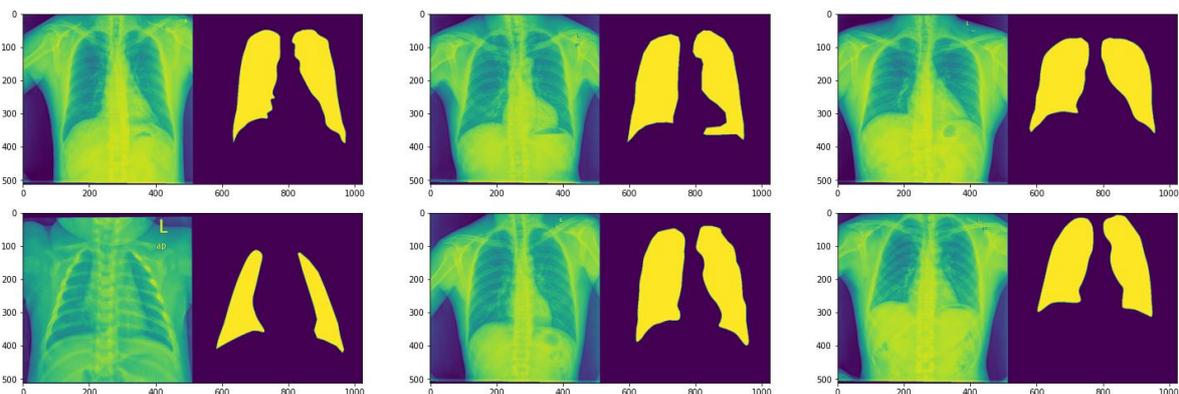
Fig.6. Chest X-Ray

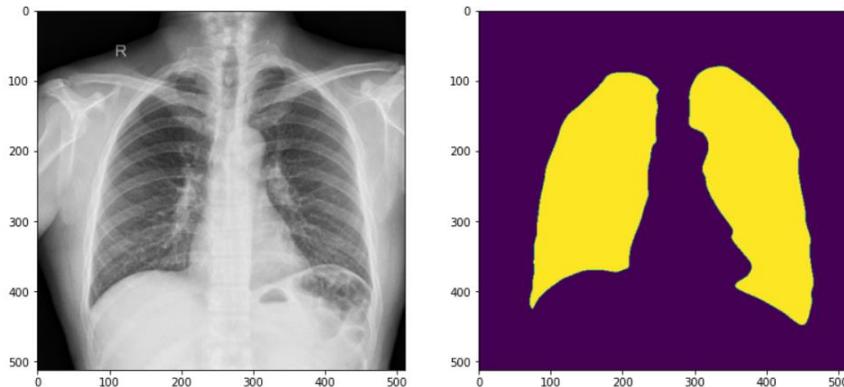

Fig.7. Masks

4.3.3 Data Preprocessing

U-Net

In data preprocessing, the dataset images resized to 512x512 and the preprocessing output is shown in Fig. 8

Fig.8. Pre-processing output

VGG11 pre-trained on ImageNet

In data preprocessing, the dataset images are resized to 512x512 and then padded and cropped and the preprocessing output is shown in Fig 9.

Fig.9. Preprocessing output

4.3.4 Lung Segmenter Model parameters

U-Net

Initial Learning Rate: The rate of learning issues can be controlled by the learning rate parameter. If it is minimum, the loss will be also minimum. For the Lung Segmenter model, the initial learning rate value is set to 0. 0002. The learning rate is shown in Fig.10.

Epochs: The number of iterations the learning algorithm go through is the Epochs. For the Lung Segmenter model, the epoch is set to 10.

Batch Size: The batch size characterizes the quantity of tests to work through prior to refreshing the internal model boundaries. For the Lung Segmenter model, batch value is set to 32. The Epochs/Batch Size are shown in Fig. 11.

```
model.compile(optimizer=Adam(lr=2e-4),
              loss=[dice_coef_loss],
          metrics = [dice_coef, 'binary_accuracy'])
```

Fig.10. Learning Rate

```
loss_history = model.fit(x = train_vol,y = train_seg,
                batch_size = 8,
                epochs = 10,
                validation_data =(test_vol,test_seg) ,
                callbacks=callbacks_list)
```

Fig.11. Epochs and Batch Size

VGG11 pretrained on ImageNet

Initial Learning Rate: The rate of learning issues can be controlled by the learning rate parameter. If it is minimum, the loss will be also minimum. For the Lung Segmenter model, the initial learning rate value is set to 0. 0002. The learning rate is shown in Fig. 12.

Epochs: The number of iterations the learning algorithm go through is the Epochs. For the Lung Segmenter model, the epoch is set to 8.

Batch Size: The batch size characterizes the quantity of tests to work through prior to refreshing the internal model boundaries. For the Lung Segmenter model, the batch value is set to 4. The Epochs and Batch Size are shown in Fig. 13.

```
unet = unet.to(device)
optimizer = torch.optim.Adam(unet.parameters(), lr=0.0002)
```

Fig.12. Learning Rate

```
batch_size = 4

train_log_filename = "train-log.txt"
epochs = 8
best_val_loss = np.inf
model_name = Path('/content/drive/MyDrive/Lung-Segmentation-master/models/unet-6v.pt')
```

Fig.13. Epochs and Batch Size

5. Results

The loss and the accuracy plot have been plotted. Lung Segmenter's training accuracy and loss curves demonstrate high accuracy and little signs of overfitting on the data as shown in Fig.14 and Fig. 15. The model becomes ready to perform Lung Segmentation. The accuracy of the model obtained for U-Net is 97.63% on the dataset and for U-Net with VGG-11 encoder pre-trained with ImageNet is 98.28%.
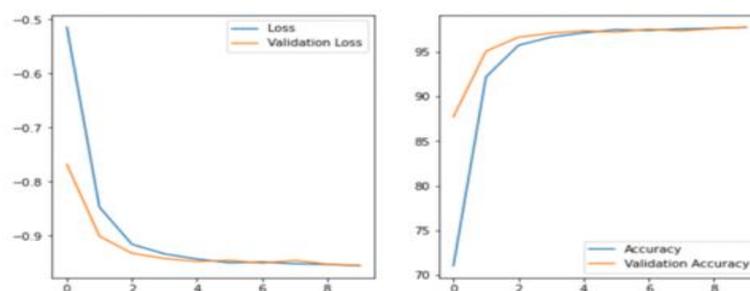
**Fig.14.** Loss and accuracy plot of UNet
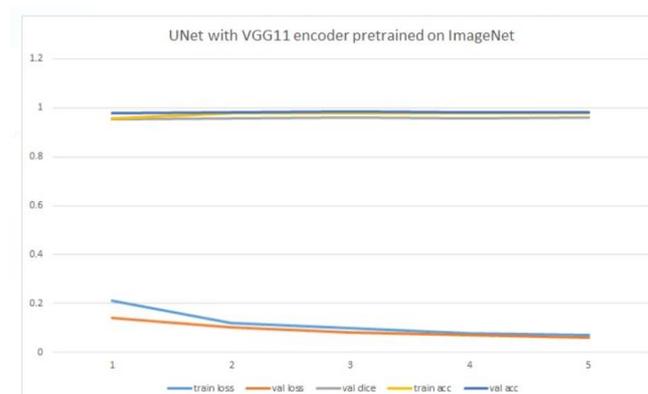
Fig.15. Loss and Accuracy of U-Net with VGG-11 encoder pre-trained with ImageNet

5.1 Comparison Between Existing and Proposed System

The comparison between the architectures such as GCN, VGG Net, HDC/DCUC, U-Net and U-Net with VGG-11 encoder pre-trained with ImageNet based on the learning rate, epochs, dice coefficient and its accuracies are shown as the following Table and Figures:

Table 1: The table compared for existing and proposed system

Architecture used	Learning rate	Epochs	Dice coefficient	Training accuracy (%)	Testing accuracy (%)
Existing system					
GCN	4e-5	30	0.9070	93.15	93.26
VGG Net	1e-4	75	0.9523	96.26	96.19
HDC/DCUC	1e-5	100	0.8501	91.42	91.23
Proposed system					
UNet	2e-4	10	0.9544	97.70	97.63
UNet with VGG-11 encoder pretrained on ImageNet	2e-4	5	0.9617	97.94	98.28
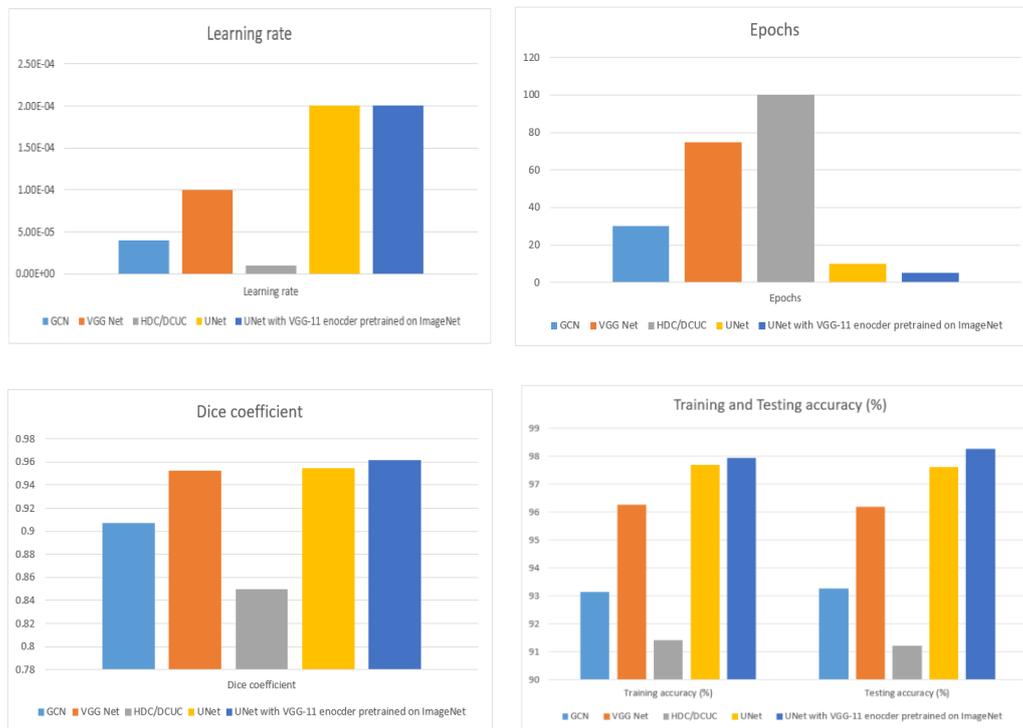
Fig.16. The graph compared for existing and proposed system

6. Conclusion

Convolutional neural network methods are attempted for segmentation of the lungs in this work. Several performance metrics such as dice coefficient, Validation and Training Accuracy were utilized in order to determine the models performance. Also compared the UNet architecture and the UNet with VGG-11 encoder pre-trained

with ImageNet with the other architectures such as GCN, VGG Net and HDC/DCUC. The higher accuracy obtained is 97.63% for UNet and 98.28% for the UNet with VGG-11 encoder pre-trained with ImageNet respectively.

Declarations

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Competing Interests Statement

The authors declare no competing financial, professional and personal interests.

Consent to participate

Not Applicable

Consent for publication

We declare that we consented for the publication of this research work.

Availability of data and material

Authors are willing to share data and material according to the relevant needs.

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