

A Modified Convolutional Neural Networks Model for Medical Image Segmentation

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Abstract

Medical image segmentation is a crucial step in developing computer-Aided Diagnosis (CAD), which supports the physician to adopt a suitable procedure about the clinical case. Lung cancer, Tuberculosis, and Pneumonia are the most dangerous threats that attack the human lungs and result in high global mortality. Precise lung segmentation from X-ray and Computed Tomography (CT) is a challenge due to the irregular shape and high ambiguity in lung edges with the background. This paper aims to develop a sufficient approach with robust lung segmentation, less time, and minimum processing cost. U-net is a deep convolutional neural network architecture; it is mostly designed for medical image segmentation. A standard kernels' number at each convolutional layer in U-net is utilized to abstract the wealthy data from the medical images. In this paper, we proposed a modified U-net model based on the reduction of kernels' number in each layer. The modification involves employing only 25% of the standard kernel's number to extract ROI from the chest images. We compare between the standard and modified U-net segmentation results using 263 X-ray images from Shenzhen dataset and 269 CT images from LUNA16 dataset. The experimental results indicate the contribution of our modified U-net to improve the global accuracy, Jaccard, and Dice metrics of the standard U-net by. Besides, the modified U-net takes about 30% of the standard U-net time to learn the network and build the proposed segmentation model. The proposed U-net architecture with a minimized kernels' number indicates the possibility to increase the lung segmentation precision in terms of some performance metrics and decrease the network learning time in terms of mean iteration time.

Keywords: Deep learning, Convolutional neural networks, Semantic segmentation, U-net, Medical image segmentation.

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I. Introduction

Recently, deep learning methods became very popular due to the wide advancement in computer hardware power, especially in GPUs. Methods based on the Convolutional neural network (CNN) and recurrent neural networks (RNN) are applied in many kinds of research fields such as computer vision, natural language processing, voice

recognition, and achieved unprecedented results [1, 2]. CNN is one of the machine learning techniques that is widely used in computer vision. It extracts the information based on the homogeneity in the region of interest (ROI) pixels from MRI, CT, and X-Ray images [3-6]. Medical images analysis is one of the applications that utilize the advances in deep learning methods, in which promising results

were obtained in a wide range of tasks, such as lung segmentation [7-10].

Recent researches indicated that the yearly ratio of tuberculosis new cases was about 10.4 million, and 1.7 of them died. Therefore, early diagnosis of any disease leads to early and successful treatment [11-13]. Developing an automated system is necessary to detect lung diseases accurately and quickly because the manual diagnoses are lack of detecting lung cancer at its early stage. [14]. The irregular and non-uniform shapes of organs and lesions, as well as the high gradually change in pixel intensity, which makes the process of edge or border detection harder [15, 16]. The standard U-net based on CNN is proposed by Olaf Ronneberger et al., [17]. The architecture of U-net consists of two contracting paths: Encoder and Decoder. The Encoder is a set of convolution and max-pooling layers that are used for down-sampling the feature maps. While the Decoder has a set of transposed convolution layers for up-sampling the feature maps. In this work, we proposed a modified U-net architecture to achieve precise lung segmentation from CXR and CT images. This modification proved that the standard U-networks more effectively by reducing 50% of its standard kernels. These kernels (filters) are responsible for feature mapping by convolving the input image. This reduction is a significant factor in reducing the proposed model complexity and hence reducing the learning time and processing costs.

The paper is organized as follows; the first section is an introduction to the main concepts. Section two discussed the theory of deep learning and related works. Section three presents a detailed description of the proposed model. Section four contains the experimental results, and comparison is used to evaluate the proposed scheme. Finally, section five presents the conclusions of this paper is presented.

II. Related Works

Neural networks are an important field of machine learning algorithms and considered as an origin of deep learning methods [18, 19]. The Multi-Layer Perceptron (MLP) is the essential neural network, consists of a set of neurons with

some activations and parameters; these neurons are organized in three layers layout: input, hidden, and output layer, as shown in fig 1. Increasing the number of hidden layers will expand the depth of the network and increase the number of weights; therefore, it is called a deep neural network or deep learning [20-22].

Deep Learning is a sub-field of machine learning techniques. The deep neural network weights can be tuned during the learning operation to solve the complex, non-linear problems [23, 24]. Deep Learning consists of many algorithms that are used for supervised learning, such as classification, and unsupervised learning, such as regression [2, 25,

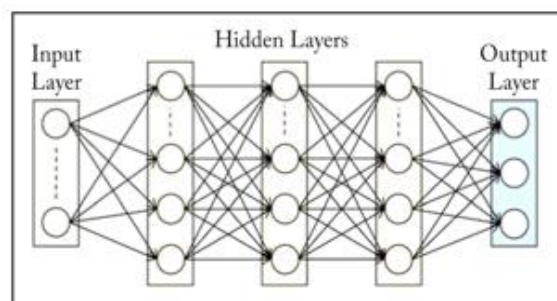


Fig 1: MLP with Three Hidden Layers [18].

26].

CNN is one of the wide used deep learning methods that manipulate high-dimensional data such as videos and images. CNN layers are divided into three sets: Convolutional layers, pooling layers, and fully-connected layers, as shown in fig 2 [27].

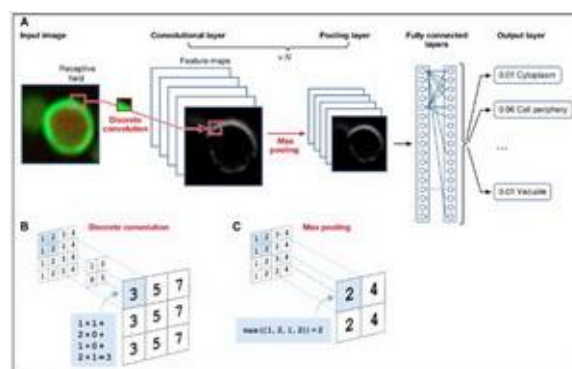


Fig 2: CNN Layers Operations [20].

Convolutional layers contain a large number of two-dimensional kernels (also called filters) that extract information from input feature maps. This

operation includes multiplying the filter weights by the corresponding image matrix values. The low-level features are extracted at the initial layers. As well as the high-level features are extracted as going on deeper throughout the CNN [28]. The pooling layers have many two-dimensional filters that receive the feature maps from the convolutional layer then reduce these feature maps depending on the pooling functions such as max, min, and average [21]. The fully connected layers function is similar to that in the feed-forward network. Each extracted feature by the pooling layer is connected to all neurons in a fully connected layer. The fully connected layer is designed according to the task that it should perform. Depending on the application, the activation function (Logistic, SoftMax, or linear) is identified to perform classification or regression tasks [29].

Nowadays, Semantic image segmentation is widely used in applications such as object robot vision, medical purposes, and autonomous driving. Deep learning has seen huge success lately in handwritten digit recognition, speech, categorizing whole images, and detecting objects in images [30]. E. Shelhamer et al., [31] propose a Fully Convolutional Network (FCN) that utilized CNN to predict the dense outputs from arbitrary-sized inputs. The image pixels are classified and identified in the spatial domain. The modification from CNN to FCN is performed by replacing the fully connected layer with an equivalent convolutional layer. Ronneberger, Olaf, et al. [17] proposed U-Net architecture as an extension of FCN. U-Net was trained using a few training images and more precise segmentation. U-net network consists of two symmetric paths, encoder, and decoder. The encoder (sometimes known as down-sampling) contains CNN that minimizes the spatial dimension to extract feature maps using successive sets of convolution and max-pooling layers. The Decoder (sometimes known as up-sampling) consists of a transposed convolutional layer, skip connections with the corresponding layer in the decoder path, and convolution layer. These layers halve the number of features and recover the spatial domain to apply pixel-wise semantic segmentation.

Recently, The development of medical and biological techniques provided a vast amount of data, such as medical images, electroencephalography, genomic, and protein sequences [2]. Medical image analysis manipulates the image data to provide relevant information for solving clinical problems. However, Image analysis is divided into preprocessing, data reduction, and feature analysis. Data reduction Image segmentation is an essential part of medical image analysis [32, 33]. L. Luo et al. [34] built a retinal blood vessel segmentation model based on modified U-net CNN. The modification involved reducing the convolutional layers to 13. The model was applied to 40 retina images with its labels from the DRIVE dataset. T. Tran et al. [35] applied SegNet encoder and decoder architecture in cutting-edge segmentation techniques. This technique applied to blood smear images from the ALL-IDB1 dataset to perform white blood cells (WBCs) and red blood cells (RBCs) segmentation. T. Yang et al. [36] proposed an automatic MRI brain tumor segmentation algorithm based on U-net architecture with. The algorithm segments each image in the brain tumor segmentation (BraTS) dataset into five regions. D. Q. Zeebaree et al. [37] proposed a new technique based on region growing and neural networks to segment the ROI of breast cancer from 250 ultrasound scans. Accurate ROI segmentation enables to diagnose whether breast cancer is benign or malignant. The proposed technique involves two stages: extracting many batches from ROI and background to build a training model, detecting the ROI from the background. The results indicate a successful ROI segmentation of the breast contour.

S. Alheejawi et al. [38] utilized the SegNet pre-trained CNN model to detect the melanoma region, which is the most dangerous kind of skin cancer. The proposed technique measures the Proliferation Index (PI) in the lymph node biopsy, which is the most important indicator to detect the cancer spread in the human body. A. Srivastava et al. [39] utilized a deeper CNN technique to detect gastrointestinal diseases from high-resolution biopsy images. The images are extracted from whole slide images (WSIs); this operation splits each slide to approximately 250 patches of 1000x1000 image size with 750 pixels overlapping

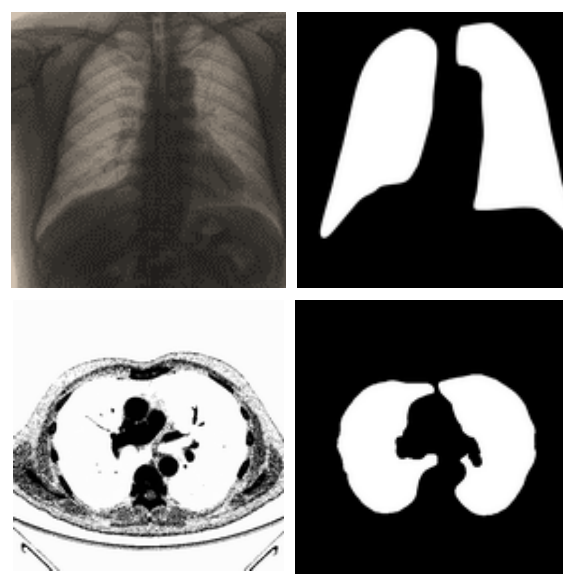
horizontally and vertically. After that, the images sizes are resized to 256x256 for feeding to the deeper CNN. The residual network (ResNet) overcomes the vanishing and exploding gradients problems by using skip connections. D. Q. Zeebaree et al. [40] used CNN as a diagnosing tool to identify and classify the gene information of the cancer microarray data. CNN prove its accuracy and the ability to minimize gene in cancer classification comparing with other techniques. L. Saidy et al. [41] proposed SegNet architecture to segment the left and right lung separately in CXR images in the Japanese lung nodule dataset. The model is evaluated with the dice coefficient, sensitivity, specificity, and Hausdorff distance. The results indicate that the developed model can be applied in real life. Hooda et al. [42] proposed a CAD system for CXR analysis. The lung field segmentation is a pre-requisite step to precisely define ROI and is subsequently used by other stages of the CAD system. They present a variant of a fully convolutional network that performs segmentation of lung in CXRs. Mittal et al. [43] proposed an LF-SegNet model based on encoder-decoder architecture to segment lung fields from CXR images. The method was tested in the JSRT and MC datasets. Johnatan Carvalho Souza et al. [44] proposed AlexNet CNN to classify 138 CXR images with 512x512 dimensions from the Montgomery Country (MC) dataset. The images are divided into 32x32 patch and then performing initial segmentation using to lung or non-lung according to specific criteria. Amit Kumar Jaiswal et al. [45] proposed a prediction method based on Mask-RCNN to segment pneumonia in CXR images that have dissimilarity in quality, brightness, and ROI position. The model utilizes ResNet50 and ResNet101 to run Mask-FCNN pretrained on the COCO dataset.

Ait Skourt, Brahim, et al. [7] proposed an early diagnosing system to detect lung cancer from CT images in Lung Image Database Consortium (LIDC). U-Net Deep learning architecture to accurately segment the lung. The performance of the model is measured using the Dice coefficient, which was 95.02%. Y. Chunran. [46] proposed FCN architecture to segment lung nodules from CT images in (LIDC) dataset. The proposed system is evaluated using the Dice coefficient, which was

90%. Shaziya. [12] presented U-Net CNN Encoder-Decoder architecture to build a lung segmentation model from 267 CT scans. The traditional segmentation algorithms are lack of extracting the lung edges accurately because of the similar intensity value issues. The image rotation is used as one of the augmentation techniques to increase the training set. The accuracy of the proposed model was 96.78%.

III. Proposed Model

In this paper, we presented a semantic segmentation model based on the modification of the standard U-net CNN. The U-net uses a set of filters or kernels in the convolutional layers to



a.Images b. labels

Fig 3: Shenzhen and LUNA16 Dataset
Sample Images and labels.

extract the feature maps from the images during the network training. We perform a significant reduction in the number of the filters at each convolutional layer. Afterwards, the modified model is trained using two datasets separately; the minimized number of filters causes minimizing in the training time and increasing the segmentation accuracy.

Dataset

In this work, we used two datasets to investigate the performance of the modified U-net architecture. The first dataset is Shenzhen CXR standard digital image dataset from Shenzhen No.3 People's Hospital in Guangdong Medical College, China [47]. This dataset is maintained by the National Library of Medicine, Maryland, USA. The second dataset is the popular LUNA16 CT images dataset [48]. We used 263 CXR images and 269 CT images with their class labels in the network training (70% for the training, 20% for the testing, and 10% for the validation). All images were single-channel depth and different dimensional sizes. Fig 3 shows a sample of the CXR and CT images with their corresponding class labels.

Data Preprocessing

A series of preprocessing operations are performed to prepare sufficient data for network

training and testing. The lung regions (ROI) in CXR images are different in their sizes and shapes. Imbalance class issue usually occurs when the number of background class pixels is much more than the pixels of the ROI class pixel. To overcome this issue, we first crop the ROI to increase the ROI class label pixels and decrease the background class pixels, secondly, use class weighting that involves calculating the median of the frequency for class weights. The images and labels in both datasets are resized to 256x256 dimensions to reduce the training time and cost.

Model Architecture

The modified U-net model based on deep convolutional neural networks is proposed for lung segmentation from the CXR image. As shown in fig 4, The model architecture consists of two symmetric paths: Encoder (at the left) and Decoder (at the right).

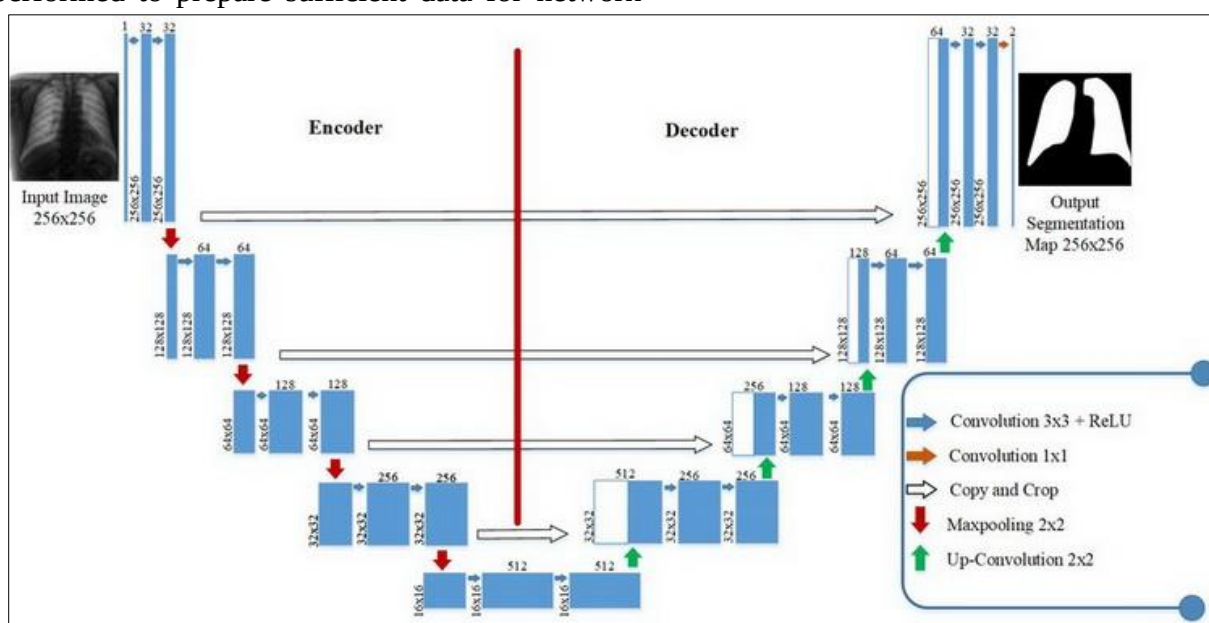


Fig 4: The Proposed U-net Architecture

The encoder is responsible for testing each pixel in the input image and deciding to which class it belongs. Also, the Decoder path recovers the original high spatial dimensional input by assigning the location of each pixel in the class label.

The encoder (also called down-sampling) path consists of four different blocks. Each block contains two convolution layers, followed by the ReLu activation function and the Max-pooling layer. The convolution layers (shown as blue bars in fig 4) use 3x3 convolution filters with stride [1 1] and padding 'same' to extract the feature map

from the CXR input images. The batch normalization is performed by the ReLu function. Max-pooling operation is shown as red arrows in fig 4; it halves the feature map dimensions using a 2x2 filter with stride [2 2] and padding '0'. The bottleneck is a part between the encoder and decoder that consists of two convolution layers with ReLu batch normalization and a 50% drop out layer.

The decoder path (also called up-sampling) consists of four expanding blocks that enables precise localization. Each block consists of an up-sampling of the feature map followed by a 2x2 transposed convolution filters that halve the number of feature channels. The depth concatenation with 2-input is used for correspondingly cropped feature map from the contracting path, and two 3x3 convolutions, each followed by a ReLu. The final convolutional layer, a 1x1, maps each 64-component feature vector to the desired number of classes.

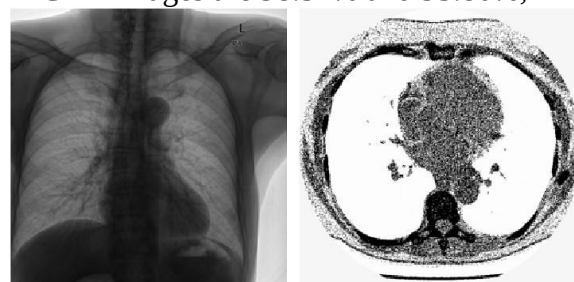
▪ Training

In the modified U-net model, we used (Shenzhen and LUNA16) datasets separately to train and test the proposed model. We used MATLAB 2019a software package with NVIDIA Quadro K110 GPU. The 'Adam' algorithm is used as an optimization function to update the network weights iteratively. We used 15 Epochs with a minimum batch size of 1. The piecewise learning rate scheduling is used with 10-3 initial learning and 0.3 Learn Rate Drop Factor' for every 10 epochs.

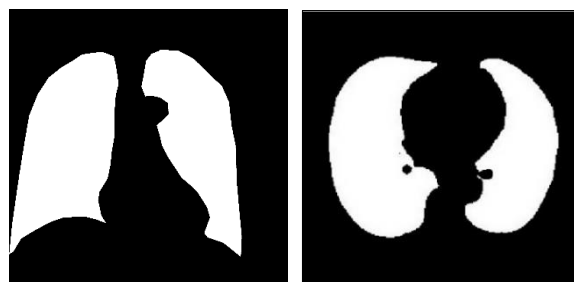
IV. Results and Discussion

The performance of our modified U-net is measured using 53 CXR images from Shenzhen dataset and 53 CT images from LUNA16 dataset separately. Figure 6-a shows the original CXR and CT images samples, as well as the expected class labels, are shown in fig 6-b. The predicted labels in fig 6-c are the result of applying our proposed lung segmentation model. We overlap the expected manual label with the predicted result label to obtain the difference between them as shown fig 6-d.

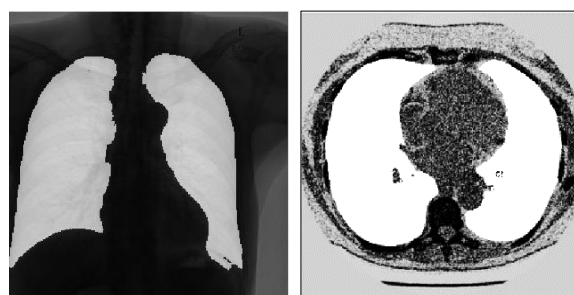
The confusion matrix in Table 1 indicates that the correctly predicted pixels for the background and lung in CXR images are 98.54% and 93.80%,



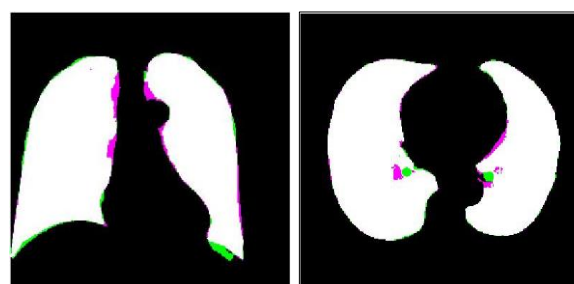
(a) Images



(b) Expected Label (Ground Truth)



(b) Predicted Label



(d) Difference Between Expected and Predicted Labels

Fig 5: The Lung Segmentation Using the Proposed Model.

respectively. The 6.2% of lung pixels predicted as background and represented as purple color in fig 6-d. While 1.46% of background pixels predicted

as lung pixels and represented as green color in fig 6-d.

Table 1: The Confusion Matrix of CXR Images Segmentation Results.

	Background	Lung
Background	98.70%	1.30%
Lung	4.85%	95.14%

The confusion matrix in Table 2 indicates that the correctly predicted pixels for the background and lung in CT images are 98.70% and 95.14%, respectively. The 4.85 % of lung pixels predicted as background and represented as purple color in fig 6-d while 1.46% of background pixels predicted as lung pixels and represented as green color in fig 6-d.

Table 2: The Confusion Matrix of CT Images Segmentation Results.

	Background	Lung
Background	98.70%	1.30%
Lung	4.85%	95.14%

However, the performance of the proposed model is measured using three metrics, the global accuracy, Jaccard coefficient, and dice index. The accuracy measures the ratio of the correctly classified pixels to the total number of pixels. The Jaccard index, also known as Intersection over union (IoU), measures the ratio of correctly

classified pixels to the total number of ground truth and predicted pixels for each class. Dice index is a statistical tool that calculates the similarity between the predicted and ground truth pixels for each class. Table 3 shows the performance metric for both datasets used in our modified U-net architecture.

Table 3: The Performance Metrics of the Proposed Model.

Dataset	Global Accuracy	Jaccard	Dice
Shenzhen CXR images	97.00%	93.37	96.57
LUNA CT images	97.90%	94.21%	97.02%

Evaluating the proposed model is an essential step to prove the ability to perform accurate lung segmentation. Therefore, we compared our modified U-net with the standard U-net in term of performance metrics and training time consumption. The comparison process involves training the standard U-net using the same datasets, preprocessing techniques, and training options as in modified U-net. In table 4, we listed the performance metrics of the standard and modified U-net in term of global accuracy, Jaccard index, and Dice coefficient.

Shenzhen CXR Dataset				LUNA16 CT Dataset		
	Accuracy	Jaccard	Dice	Accuracy	Jaccard	Dice
Standard U-net	95.61%	90.59%	95.06%	97.55%	93.20%	96.48%
Modified U-net	97.00%	93.37%	96.57%	97.90%	94.21%	97.02%

Table 1: The Comparison Between Modified U-net and the Standard U-net Performance.

Fig 7 shows the comparative analysis of the performance metrics data in table 4. The analysis focuses on the impact of our modified U-net to increase the performance of the standard U-net

with the use of Shenzhen and LUNA16 datasets. All performance metrics for both datasets shown in fig 7 have been increased as a result of our successful U-net modification.

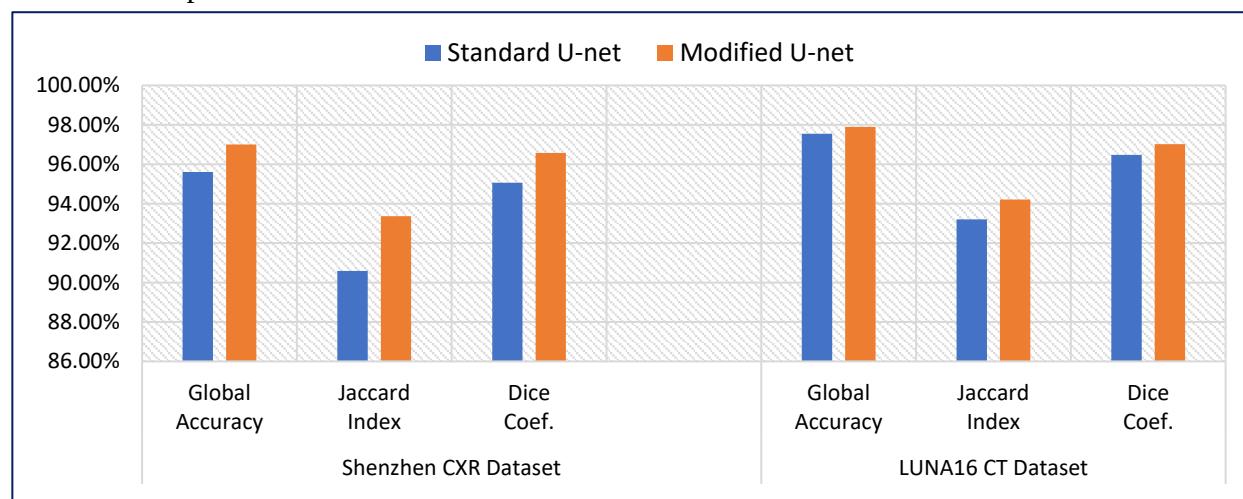


Fig 6: The Comparison Analysis of the Performance Metrics.

The other objective of our modified U-net model is to reduce the training time consumption for the standard U-net. The mean iteration time is an effective indicator to measure training time consumption. It can be calculated by dividing the training time on the total iteration numbers. Table 5 illustrates the mean iteration time for the modified and standard U-net.

time of the standard U-net model. Figure 8 shows the mean iteration time for both models when training the model using the Shenzhen and LUNA16 datasets.

Besides, we compare the performance of our

Table 5: The Comparison Between Our Modified and the Standard U-net Mean Iteration Time (Sec).

	Shenzhen Dataset	LUNA16 Dataset
Standard U-net	2.888	2.714
Modified U-net	0.838	0.843

In fig 8, we

analyzed the mean iteration time data in Table 5. The analysis demonstrates the significant impact of our modified U-net model to minimize the training

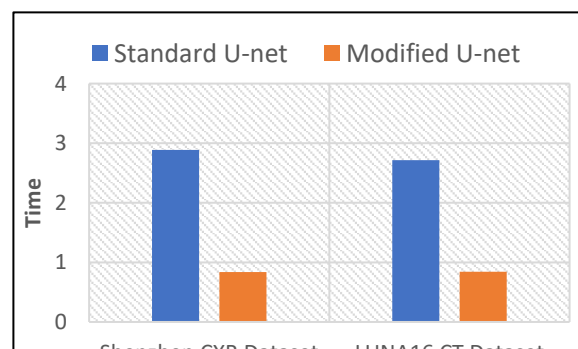


Fig 7: The Comparison Analysis of the Mean Iteration Time.

proposed with many relevant techniques, as shown in Table 5. These results indicate that the lung segmentation from CXR and CT using our proposed model achieves higher performance than other recent researches.

Table 6: The Comparison Between Our Modified and Some Other related works.

Image	Paper	Method	Dice	Accuracy
CXR	H. Trung Huynh, et al [49]	CNN+Neural Net.	87.00%	93%
	L. Saidy, et al. [41]	Encoder-Decoder CNN	95.95%	-
	Modified U-net	Modified U-net	96.57%	97.00%
CT	Ait Skourt, et al [7]	U-Net	95.02%	-
	Y. Chunran, et al [46]	FCN	90%	-
	H. Shaziya, et al [12]	U-net	-	96.78
	Modified U-net	Modified U-net	96.97%	97.87%

V. Conclusion

In this paper, we present a modified U-net deep neural network to build an accurate semantic segmentation model to extract the lung regions from CXR and CT images. Accurate lung segmentation is essential to detect the lung diseases in early stages. We increase the accuracy of the U-net architecture and reduce the training time by decreasing the number of the feature extraction kernels in the convolutional layers of the Encoder and Decoder paths. This minimization has a significant impact on reducing the time and cost of network training. Our modified U-net is trained and tested using Shenzhen CXR dataset and LUNA16 CT dataset. The obtained results are compared with the standard U-net and many other related works using many metrics. The comparison demonstrated the effectiveness of our modification in U-net to perform precise lung segmentation, which will help to make an early diagnosis for any diseases related to the human chest in the future.

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