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Semantic Segmentation of Lungs using U-Net

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Abstract

Semantic segmentation of medical images is crucial for aiding radiologists and clinicians in accurately diagnosing conditions and planning treatments. This research introduces an innovative technique for the semantic segmentation of lungs using a U-Net design. The U-Net model demonstrates outstanding performance in various medical image segmentation tasks by effectively capturing both local and global features. Additionally, Res-U-Net architecture is harnessed to identify lung regions from lungs CT images, with a focus on improving the accuracy and efficiency of the segmentation process. Python is utilized for both designing and executing the algorithm in this work. Google Colab, a popular platform, is being used for its computational resources and collaboration features. The datasets were sourced from Iraq-Oncology Teaching Hospital with 70% of the data allocated for training and 30% for testing.

Keywords: Lung segmentation, X-Ray imaging, U-Net, Semantic segmentation, Deep learning

1. Introduction

Segmentation in image processing refers to the technique of distinguishing the desired area of an image. To diagnose various diseases, particularly those related to the lungs, segmenting CT images is essential. In segmentation, the first step is to segment the lung image

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to diagnose other lung-related diseases like tumors. This can be accomplished through various segmentation methods using different algorithms. [1-3]. U-Net, used in the work, is significant for its powerful and efficient approach to image segmentation. It consists of a symmetric architecture with an encoder-decoder structure, which allows it to capture both context and precise localization. In the process of segmentation, U-Net is particularly effective in medical imaging because it can accurately delineate structures like tumors in lung CT scans. The skip connections in U-Net help retain important spatial information by directly linking corresponding layers in the encoder and decoder paths, ensuring high-quality segmentation results. [4-6].

Furthermore, ResU-Net, used in the work, combines the strengths of U-Net and residual networks. Its significance lies in its ability to enhance segmentation accuracy by addressing the vanishing gradient problem common in deep networks. ResU-Net improves feature extraction and image segmentation by incorporating residual connections, allowing for more efficient and accurate detection of structures within medical images, such as tumors in lung CT scans.

2. Literature Survey

In [7] the authors introduced a method using a patch-based 3D U-Net combined with a contextual convolutional neural network (CNN) to automatically segment and classify lung nodules. This approach aims to aid radiologists in interpreting CT images more efficiently. In [8] the authors proposed a technique for segmenting the lungs using the Chan–Vese (CV) model, combined with a Bayesian approach to detect juxta-pleural nodules. In [9] the author utilized a U-Net model for lung segmentation for chest X-Ray images, achieving competitive performance compared to other methods. The use of a random forest classifier was examined in [10] to address the challenge of unbalanced lung nodule classification. They extracted features from the lung nodules using three different feature selection algorithms: Relief, Genetic Algorithm, and Particle Swarm Optimization. In [11] the authors showcased a technique for lung nodule segmentation and classification using a thresholding approach. They applied traditional histograms and iterative thresholding to segment the lung images, followed by a rule-based filtering method to identify lung nodules. For classification, they employed KNN and SVM classifiers.

3. Methodology

The different phase of the proposed diagram is shown in Figure 1.Proposed block diagram. The Figure2. illustrates the U-Net architecture, demonstrating how the segmentation operation works in image processing [12 and 13].

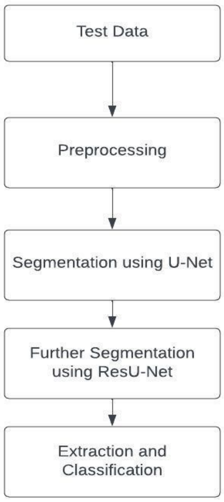

Figure 1. Proposed Block Diagram

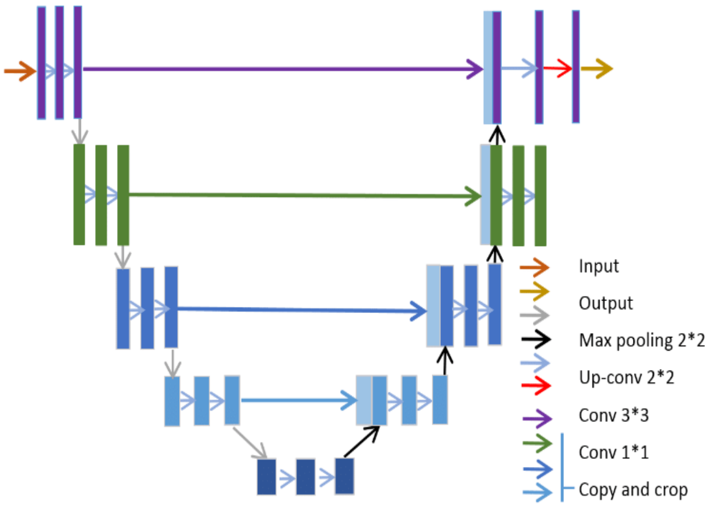

Figure 2. Architecture Of U-Net.

It comprises of two main parts: the contracting path that is encoder and the expanding path that is decoder, which together form a "u" shape, giving the network its name. The contracting path is responsible for capturing context and decreasing the width and height of the feature maps, while the expanding path is responsible for precise localization and increasing the spatial dimensions back to the original size. Additionally, this architecture includes skip connections, which is used to connecting the contracting and expanding paths, allowing the network to retain high-resolution features and improve segmentation accuracy [14 and15].

3.1 Res U-Net Architecture:

ResU-Net includes convolutional layers for feature extraction, max pooling for down sampling, residual connections for gradient flow, up-sampling for reconstruction, and concatenation with skip connections for detailed localization. These elements work together to improve the segmentation performance of the network. It incorporates residual connections, , to improve training performance and model accuracy as shown in Figure 3. The proposed technique consists of the following key components:

Encoder: The encoder section comprises several layers. these layers are adept at extracting features at different levels from the input image.

Residual blocks: Residual blocks are introduced to facilitate the training of deeper networks. These blocks contain skip connections that bypass one or more layers, allowing gradients to flow more easily during training.

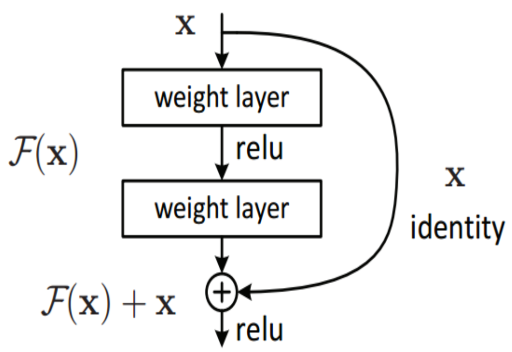

Figure 3. Architecture Of Res U-Net.

Decoder: Decoder part of the proposed architecture consists of up-sampling layers followed by convolutional layers. the decoder reconstructs the segmented lung regions from the extracted features.

Skip Connections: It connects the layers in proposed architecture to capture both level features.

4. Results and Discussion

The dataset was split with 80% and 20% for training and validation. The model was trained for 250 epochs. The average loss of the model was found to be 0.29. Figure 4 and 5 shows nodule segmented using the U-Net and Res- U-Net model.

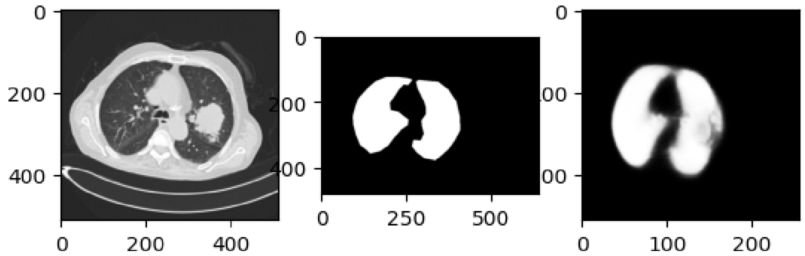

Figure 4. Output of U-Net

Table 1 presents the accuracy. This metric gives a fundamental assessment of the models performance across all classes.

Table 1. Parameters of U-Net

S.No.	Parameter	Values
1	Accuracy	0.87%
2	Loss	0.23
3	Optimizer	Adam
4	Learning Rate	1e-4
5	Loss Function	Binary_Cross Entropy

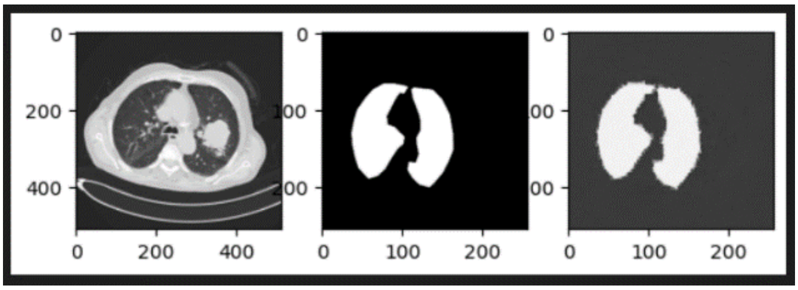

Figure 5. Output of Res U-Net

Table 2 presents the accuracy. This metric gives a fundamental assessment of the model's performance across all classes.

Table 2. Parameters of Res-U-Net

S.No.	Parameter	Values
1	Input	256 X 256 X3 Of 90
2	Output	1
3	Accuracy	97.6%
4	Loss	5.2%
5	Optimizer	Adam
6	Learning Rate	1e-4
7	Loss Function	Binary Focal Loss
8	Epochs	50

Training Loss

The model achieved a training loss of 5.2%, indicating the average error during the training epochs. This Loss Metric Provides Insights into How well the model learned to extract the lungs as shown in Figure6.

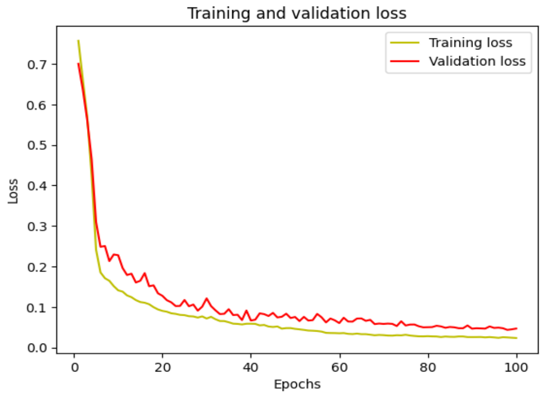

Figure 6. Model loss

Training Accuracy

The model achieved an accuracy of 97.6%, showcasing the proportion of correctly classified instances over the entire dataset. While accuracy is a fundamental metric, further examination of other metrics is essential for a comprehensive evaluation as shown in Figure 7.

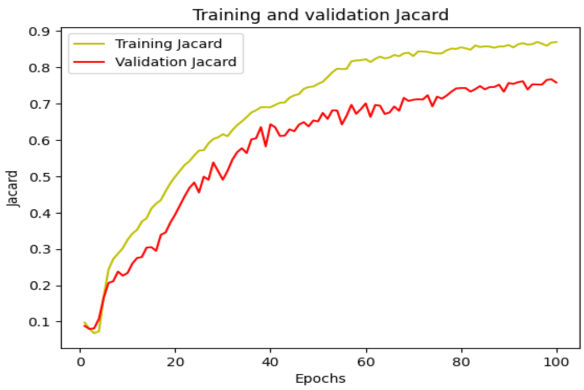

Figure 7. Model Accuracy

The comparison of the proposed method with the existing method is illustrated in Figure 8. This figure shows the progression of the loss function for both the training and validation sets, highlighting how the performance of the models evolves over time.

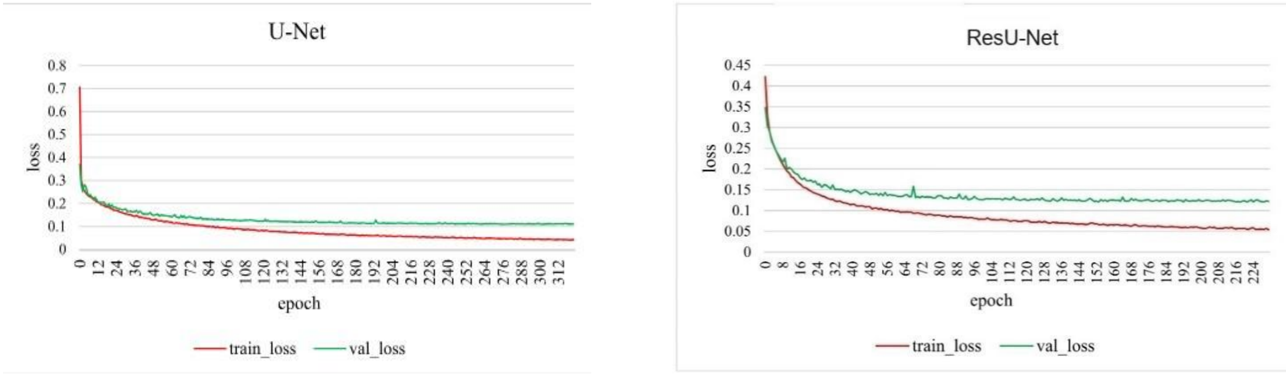

Figure 8. Plot of U-Net and ResU-Net

Table 3 represents the data samples used to segment and classify lung tumors using CT images from the Iraq-Oncology Teaching Hospital.

Table 3. Distribution of Datasets for Classification and Segmentation

Category	Number of Samples
Normal	366
Benign	366
Malignant	365
Total	1097

5. Conclusion

The work introduces a method for segmenting lung images in CT scans using the U-Net and Res U-Net architectures. Our method combines the strengths of the U-Net architecture with residual connections, allowing for the training of deeper networks and improving segmentation performance. Through a two-stage training strategy and the use of data augmentation techniques, we achieved higher segmentation. The results demonstrate the effectiveness of the proposed Res U-Net architecture in accurately segmenting lung regions from CT images. The model showed promising performance on a publicly available dataset, achieving high sensitivity, specificity, and accuracy. In the future, the research would utilize sophisticated data augmentation methods, such as generating synthetic data with GANs, to produce more varied training datasets.

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