U-Net Based Lung Segmentation: A Deep Learning Approach

Preprint · December 2023

DOI: 10.13140/RG.2.2.11728.07686

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Abstract

Since lung cancer is a serious threat to people's lives and health, precise lung region segmentation is essential for tumor localization and efficient image processing. We present a new method for lung image segmentation in this work, which makes use of the U-Net architecture, which is well-known for its efficiency in deep learning-based [1]image segmentation. The U-Net model is well-known for its effective encoding and decoding abilities. It is skilled in reconstructing intricate segmentation maps and extracting high-level features. We added a post-processing step to improve the segmentation results even more by removing unnecessary components from the segmentation output. Our U-Net based model obtained remarkable segmentation accuracy after extensive testing, including modifications in the amount of training epochs, with a Test Intersection over Union (IoU) score of 0.8904. This performance marks a significant advancement in the state-of-the-art for lung segmentation.

Index Terms— Lung Segmentation, U-Net Architecture, Deep Learning, Image Segmentation, Medical Imaging.

1. Introduction

The incidence and mortality rates of lung cancer, one of the most deadly types of malignant tumors, have dramatically increased globally, presenting a serious threat to public health. Many countries have seen a significant increase in lung cancer occurrences over the past fifty years, continuously ranking lung-related disorders among the top causes of death, especially in the United States. Given the high treatment success rate associated with early diagnosis of lung cancer, the importance of early identification and prevention cannot be emphasized[4].

Typically, unchecked cell growth inside lung tissue is the cause of lung cancer[3]. Early diagnosis is critical because treatment success rates for early-stage lung cancer have been found to approach 90% in clinical settings. The chances of patient survival can be increased and death rates can be significantly reduced with this early intervention[6]. Chest X-rays (CXR) are often used for screening purposes for pneumonia and lung cancer. However, the diagnostic process might be complicated by factors that considerably alter CXR clarity, such as breathing depth and patient location. The difficulty is exacerbated by the large number of photos that physicians must evaluate, which emphasizes the need for automated segmentation techniques to support precise diagnosis and efficient treatment planning.

Several methods for lung segmentation have been developed in the field of medical image analysis. Artificial neural networks, genetic algorithms, thresholding, region-based techniques, level set techniques, and genetic algorithms are a few of these. Every one of these techniques has a different strategy and purpose. For example, thresholding methods—both global and adaptive thresholds—create binary images by using gray value intervals to distinguish between target and background regions. Conversely, level set approaches use the progression of curve motion to pinpoint image borders, gradually shifting curves across different image regions to define three-dimensional surfaces.

This context lays the groundwork for the creation and implementation of advanced picture segmentation methods that will improve the effectiveness of lung cancer diagnosis and therapy[5]. One such method makes use of the latest developments in artificial neural networks.

Deep neural networks have significantly enhanced the field of image segmentation, outperforming many classical techniques[2]. A comprehensive review by Garcia highlighted the strides made in deep learning-based segmentation methods [7]. Among the various architectures developed for segmentation tasks, the Fully Convolutional Network (FCN) [5] marked a pioneering approach, enabling end-to-end segmentation and efficient processing of images of varying sizes. This architecture set a precedent for subsequent advancements but had its limitations, particularly in managing high-resolution images and real-time segmentation challenges.

A crucial challenge in using CNNs for segmentation is the pooling layers, which, while expanding the receptive field, can obscure precise location information critical for semantic segmentation. To overcome this, encoder-decoder structures like SegNet [9] and U-Net [12] have become prevalent. These architectures typically involve modifying a classification network (like VGG-16), removing its fully connected layers to create a feature map (the encoder), and then using a decoder to map these features to pixel-level predictions. The variations in encoder-decoder designs are primarily in the decoder's architecture.

Dilated convolutional layers have also been used to eliminate the need for pooling layers. The DeepLab model by Chen et al. [11] is an example, employing atrous convolutions and a fully connected conditional random field for atrous spatial pyramid pooling (ASPP).

In our study, we present a lung segmentation model leveraging the U-Net architecture, a well-established encoder-decoder framework in deep learning-based image segmentation. The U-Net model is uniquely designed to retain critical location information and efficiently segment lung images. Our network achieved impressive segmentation accuracy, demonstrated by a 0.9345 dice score.

Our contributions are threefold:

1. We adapted the U-Net architecture for high-precision segmentation of chest radiographs.
2. We introduced a novel post-processing layer to the U-Net, designed to filter out minor inaccuracies in the segmentation results.
3. The proposed model demonstrated superior performance in terms of dice and IoU scores, surpassing existing state-of-the-art models.

2. Methods

2.1. U-Net Architecture

Our proposed model is built upon the U-Net architecture, a widely recognized convolutional neural network (CNN) for medical image segmentation. U-Net is particularly suited for biomedical image segmentation due to its ability to work with limited data and produce precise segmentations.

Encoder: The model's encoder is designed to extract and downsample features from the input images. It consists of four `encoder_block` modules, each containing two convolutional layers with batch normalization and ReLU activation, followed by a max-pooling layer for downsampling. The input channels gradually increase from 64 to 512 across these blocks, enabling the model to capture a rich set of features at various scales.

Bottleneck: At the heart of the network is the bottleneck, a `conv_block` that processes the deepest, most compressed representations. This block is crucial for capturing the most abstract features of the input.

Decoder: The decoder part of the network is responsible for upsampling the compressed feature maps and restoring them to the original image size. Our model employs a `CustomUNetDecoder` consisting of four `CustomDecoderBlock` modules. Each module begins with an upsampling layer followed by convolutional layers, batch normalization, and ReLU activation. The upsampled features are combined with the corresponding encoder features to preserve spatial information, crucial for accurate segmentation.

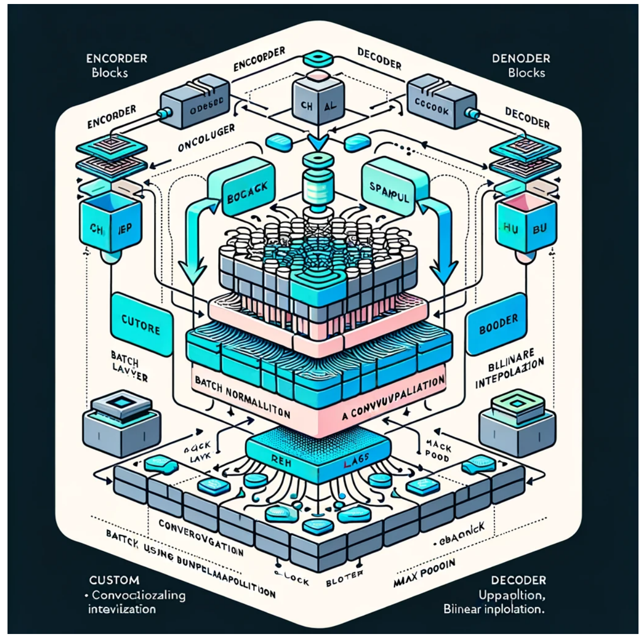


Figure 1. U-Net Architecture

2.2. Post-Processing Layer

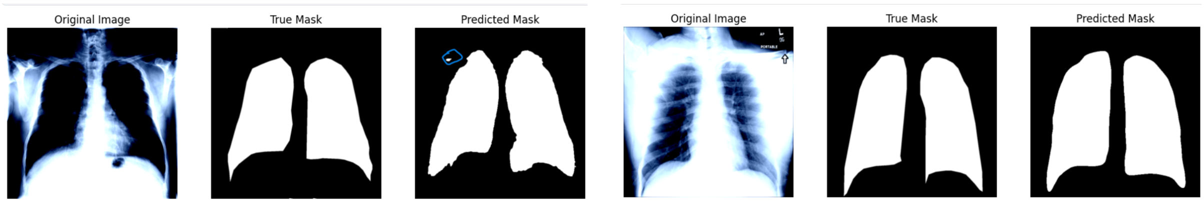
To refine the segmentation results further, we have introduced a novel post-processing layer within our U-Net model. This layer operates on the output masks generated by the decoder.

Functionality: The post-processing layer applies a thresholding operation to the output masks to enhance the segmentation quality. Masks with pixel values above 0.5 are retained, while others are set to zero. This step is crucial for removing minor inaccuracies and ensuring cleaner, more precise segmentation boundaries.

2.3. Implementation

The complete model build_unet_with_postprocessing inherits from the base U-Net architecture (`build_unet`) and integrates the post-processing functionality. We use the forward method to pass the input through the encoder, bottleneck, and decoder, and subsequently through the post-processing layer.

Experimental Setup: For experimental purposes, the model was instantiated and tested with synthetic data to validate its architecture. A random tensor of shape `(2, 3,`



(a) Image Before Post-Processing Layer (b) Image after Post-Processing Layer

Figure 2. Comparison of images before and after Post-Processing Layer

512, 512) was used to simulate a batch of two RGB images, each of size 512x512. The output of the model was observed to ensure the expected behavior and shape.

3. Discussion

The initial approach in our segmentation model involved the use of data augmentation techniques to enhance the diversity and robustness of our training data. This strategy included a series of transformations such as resizing images to 512x512 pixels, normalizing them, and applying augmentations like Color Jitter for brightness, contrast, and saturation adjustments, Gaussian Blur, and standard normalization. These steps were crucial in preparing our dataset for effective training and generalization.

Despite these efforts, the model's performance before introducing the Post-Processing Layer, as evident in our five-fold cross-validation results, indicated room for improvement. At epoch 10, the model achieved a Test Dice score of 0.9195 and a Test IoU of 0.8536, with a Test Loss of 0.1203. These results, while promising, suggested that further enhancements were needed to achieve optimal segmentation precision.This result you can see in the Table 1. The subsequent integration of the Post-Processing Layer marked a significant turning point in the model's performance. Post-Processing significantly refined the model's output, leading to a notable improvement in key metrics. At epoch 10, with the Post-Processing Layer, the Test Dice coefficient increased to 0.9394, and the Test IoU improved to 0.8904, while the Test Loss decreased to 0.0898. These improvements underscore the layer's effectiveness in enhancing the model's accuracy and its crucial role in handling complex segmentation tasks.This result you can see in the table 2.

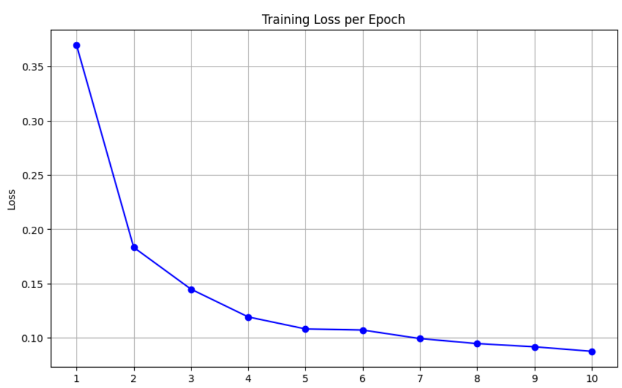


Figure 3. Losses over epoch

Table 1. Five-fold cross-validation segmentation results without Post-Processing Layer

Epoch	Test Loss	Test Dice	Test IoU
5	0.1045	0.9281	0.8666
7	0.1010	0.9305	0.8715
10	0.1203	0.9195	0.8536

Table 2. Five-fold cross-validation segmentation results with Post-Processing Layer

Epoch	Test Loss	Test Dice	Test IoU
5	0.1045	0.9281	0.8666
7	0.1010	0.9305	0.8715
10	0.0898	0.9394	0.8904

The comparison between the results obtained with only data augmentation and those achieved after the introduction of the Post-Processing Layer clearly demonstrates the value added by this layer. It not only refines the outcomes but also significantly boosts the model's overall predictive performance. This enhancement is particularly vital in segmentation tasks where precision is of utmost importance. The consistent improvement across various metrics reinforces the Post-Processing Layer's role as a pivotal component in our segmentation model.

4. Conclusion

The goal of this study was to investigate the efficacy of U-Net architectures in picture segmentation tasks, with a particular emphasis on getting high Intersection over Union (IoU) scores. The major findings clearly show that U-Net may greatly improve segmentation accuracy when augmented with data augmentation approaches and a Post-Processing Layer. Notably, the model exceeded the initial aim of 0.85 by achieving an amazing IoU of 0.8904. This accomplishment is a huge step forward in the pursuit of quick and accurate image segmentation.

These findings have far-reaching ramifications. The improved U-Net model's ability to segment images reliably lays the path for more precise and reliable image analysis in a variety of applications. This might include everything from medical imaging, where correct segmentation is critical for diagnosis and treatment planning, to remote sensing and astronomical observations, where detailed picture analysis is essential.

Finally, incorporating data augmentation and a Post-Processing Layer into the U-Net design has proven to be a reliable technique for increasing segmentation accuracy. The achieved IoU of 0.8904 demonstrates the efficacy of these enhancements. This research not only adds to the field of picture segmentation, but it also establishes a precedent for future research in this area. The final anticipated masks, as shown in the in figure 2, demonstrate the methodological enhancements' practical utility in real-world circumstances.

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