

Research Article

Segmentation Performance Analysis of Transfer Learning Models on X-Ray Pneumonia Images

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Abstract: Segmentation of pneumonia areas on chest X-rays is essential to improve the accuracy of recognition tasks and subsequent diagnosis. The capabilities of deep learning techniques, U-Net, SegNet, and DeepLabV3, are assessed to achieve these purposes. Using transfer learning, these models were adapted to pneumonia-specific datasets. The evaluation focuses on Intersection over Union (IoU) and accuracy metrics. Results show that DeepLabV3 outperforms U-Net and SegNet, achieving 84.4% accuracy and 81% IoU. U-Net achieves 80.3% accuracy and 68% IoU, while SegNet achieves 81.0% accuracy and 70% IoU. These findings highlight the potential of transfer learning models to automate the segmentation of pneumonia-affected regions, thereby facilitating timely and accurate medical intervention.

Keywords: Deep Learning; DeepLabV3; Pneumonia Segmentation; SegNet; U-Net.

1. Introduction

Segmentation methods are integral to analyzing and interpreting medical images, particularly in diagnosing and treating diseases like pneumonia. Pneumonia, a significant global health issue, is characterized by inflammation of the lung tissue, primarily affecting the alveoli. Accurate and efficient identification of pneumonia-affected regions in chest X-rays is crucial for timely and effective treatment. Previous research on pneumonia detection using machine learning techniques has shown promise but often yielded less than optimal performance, primarily due to the lack of a robust segmentation process [1], [2]. Without effective segmentation, the models struggled to isolate pneumonia-affected regions accurately, leading to suboptimal diagnostic accuracy.

Traditional image segmentation techniques, such as thresholding, edge detection, and region growing, have been widely used in medical imaging to isolate areas of interest within an image. Thresholding is simple and computationally efficient but often fails in images with varying intensity levels. Edge detection can accurately capture boundaries but is sensitive to noise and often requires additional processing to achieve reliable results. Region growing is intuitive and effective for homogeneous regions but can be computationally intensive and struggles with images containing noise or artifacts. Recent advances in machine learning, particularly deep learning, have revolutionized the field of image segmentation. Convolutional Neural Networks (CNN) have demonstrated exceptional performance in image analysis tasks due to their ability to learn and extract hierarchical features from data [3], [4]. Transfer learning, a technique where a pre-trained model is fine-tuned on a specific task, has emerged as a powerful approach in medical image segmentation. By leveraging pre-trained models on large datasets, transfer learning can significantly improve the accuracy and efficiency of segmentation tasks, even with limited medical image data.

In this work, we explore the application of transfer learning for pneumonia segmentation in chest X-rays using three state-of-the-art deep learning models: DeepLabV3 [5], SegNet [6], and U-Net [7]. By fine-tuning these pre-trained models on a pneumonia-specific

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dataset, we aim to enhance segmentation accuracy and facilitate more reliable detection and diagnosis of pneumonia. This approach not only leverages the strengths of deep learning but also addresses the challenges posed by traditional segmentation methods and the shortcomings of previous recognition research lacking robust segmentation processes. By employing DeepLabV3, U-Net, and SegNet, we aim to compare and evaluate their effectiveness in delineating pneumonia-affected regions, contributing to ongoing advancements in medical image analysis. The primary objectives of this research include:

1. Implementing and fine-tuning DeepLabV3, U-Net, and SegNet for pneumonia segmentation in chest X-ray images.
2. Conducting a comparative analysis of the performance of these architectures in terms of Intersection over Union (IoU) and accuracy.
3. Providing insights that can guide healthcare professionals, researchers, and developers in selecting appropriate models for pneumonia detection in clinical settings.

The structure of this paper is as follows: Section 2 provides a review of related literature. In Section 3, the proposed deep-learning model for pneumonia segmentation is described. Section 4 presents the performance evaluation results, and Section 5 concludes the study.

2. Literature Reviews

2.1. Related Works

Segmentation takes parts as the critical portion for providing accurate analysis operations. This process is particularly crucial in analyzing medical images like X-rays, where extracting tissues, organs, and pathological structures is imperative. Nevertheless, the segmentation of medical images, especially in X-rays, poses considerable challenges due to unique characteristics such as contrast, blur, and noise.

A fully Convolutional Attention Network (FCA-Net) based lung segmentation approach was introduced by combining channel and spatial attention to the Res2Net encoder to illustrate features with Qatar university's chest X-rays images [8]. These chest X-ray images are divided into 10% testing and 90% training. Cross-validation is carried out by employing the values of k to 2 to 10. The most accurate output is achieved at the value of k is 5. In this configuration, the Dice Similarity Coefficient (DSC) achieved a notable value of 97.24%, indicating high similarity between the predicted and ground truth masks. Additionally, the Intersection over Union (IoU) reached 94.66% in the testing data, signifying a robust performance in accurately delineating lung regions in chest X-ray images.

Al Reshan et al. [9] introduced a deep-learning approach to identify normal and serious events of pneumonia with eight transfer learning approaches: ResNet50, DenseNet201, VGG16, MobileNet, ResNet152V2, Xception, EfficientNet, and ResNet152V2, and the system was evaluated with 5856 and 112,120 chest X-ray images. Among them, the MobileNet model provided the most promising accuracy by 94.23% and 93.75%.

Rahman et al. [10] introduced a deep learning framework-based divide and conquer strategy for segmenting chest X-ray images by employing a deep ensemble strategy of two approaches: conventional CNN for image patch classification and modified U-Net for patch segmentation. The combination of each output is done with binary disjunction for initial segmentation. This segmentation is refined with dilation, region-filling, erosion, and connected component labeling for final segmentation. Two datasets (MC, JPCL) and one proprietary dataset at the University of Texas medical branch were used. The utilization of these datasets showcases the versatility and effectiveness of the framework in achieving accurate lung region segmentation across varied image sources.

Another research [11] introduced the lung segmentation system with Deeplabv3+ such as Mobilenetv2 and Resnet18. It provided the top-tier accuracy by 99.37%, 99.09%, and 98.31% on JSRT, MC, and Shenzhen datasets. These results surpass the capabilities of current state-of-the-art methods in the field. This database constitutes healthy and unhealthy of lung abnormalities. This segmentation approach illustrates robustness with various serious events. This adaptability enhances its applicability in real-world clinical settings.

Training a deep CNN from scratch poses challenges due to the significant computational time, the need for a large labeled dataset, and substantial expertise. As an alternative, fine-tuning a pre-trained CNN using a substantial set of labeled medical datasets has proven practical. This paper presented a comparative study that explores the performance of pre-

trained models, specifically VGG-19 and Res-Net-50, in contrast to training a CNN from scratch [12]. To mitigate overfitting, the study incorporated data augmentation and dropout regularization techniques. The analysis illustrated that fine-tuned pre-trained models provided the recall by 92.03% with CNN trained from scratch by highlighting pre-trained models outperform in medical image analysis tasks, where obtaining large labeled datasets and computational resources for training from scratch may pose significant challenges.

Research [13] presented a precise and robust automatic lung segmentation method based on the U-Net architecture. The methodology incorporates a pre-trained Efficientnet-b4 as the encoder and optimizes the decoder using residual blocks and LeakyRelu activation. This method provided a Jaccard Index of 95.8% for JSRT and 95.5% for MC datasets. For further validation, a dataset was created from the NIH Chest X-ray dataset containing random 2785 images with 16 different situations. Experienced radiologists manually annotated the lung areas in these images. The proposed model was then employed to evaluate the segmentation performance on this Haut dataset, yielding an impressive overall Jaccard Index of 97.4%.

A study [14] presented a U-Net approach for insufficient feature extraction in the segmentation of lungs. This approach developed the FVAE model with Variational Auto-encoder (VAE) to the convolutional layer, which can enable the capturing of detailed local information and global context by applying three-terminal attention of channel and spatial attention modified for high-scale features. These mechanisms are capable of localizing and enhancing recognition in segmentation. This is evaluated with SNIH and JSRT datasets, and the results illustrated it outperforms than other approaches in terms of accuracy, recall, and f1-Score.

Research [15] introduced a robust model tailored for the segmentation of lungs in chest radiographs. The key innovation of our model lies in its adeptness at discerning and disregarding unimportant areas within the source chest radiograph while simultaneously accentuating crucial features essential for accurate lung segmentation. This strategic approach enables our model to overcome inherent challenges associated with complex radiographic images. To validate the model's efficacy, they evaluated widely used public datasets, specifically the Montgomery and Shenzhen datasets. The outcomes of these evaluations underscore the model's exceptional performance, as indicated by a DICE coefficient of 98.3%. This high DICE coefficient attests to the reliability and accuracy of our proposed model in effectively delineating lung structures within chest radiographs.

Silva et al. [16] described an innovative multi-network ensemble method incorporating a selector network, offering an advanced approach to lung segmentation. The selector network is pivotal in evaluating the segmentation outputs of networks. This lung segmentation network comprises five encoder paths U-Net and two backbones (ResNet50 and Res-Net18) DeepLabv3+. The selector network is constructed with ResNet18 architecture. All training processes were conducted using the publicly available Shenzhen CR dataset. It was experimented with Montgomery County (MC) and the Japanese Society of Radiological Technology (JSRT) datasets. It showed that it achieved the Intersection-over-Union scores by 13% on MC and 5% on JSRT.

Study [17] evaluated a U-Net architecture on a dataset comprising 565 X-ray images, further divided into 500 images for training and 65 for validation. The experimental findings highlight the effectiveness of the proposed strategy, showcasing competitive outcomes. Specifically, the results indicate an accuracy of 91.47% and 89.18%, IoU (Intersection over Union) values of 0.7494 and 0.7480, and loss rates of 19.23% and 26.11% for the training and validation images, respectively. These metrics emphasize the success of the proposed U-Net architecture in achieving accurate and robust segmentation on X-ray images, demonstrating its potential for practical applications in medical image analysis.

While there was significant progress in pneumonia segmentation using traditional and deep learning methods, there are various gaps. Many traditional methods lack the robustness and accuracy required for reliable medical diagnosis, particularly in the presence of image noise and variability. Despite their superior performance, deep learning approaches often require large annotated datasets and substantial computational resources, which are not always available in medical settings [18], [19]. Moreover, previous research on pneumonia detection has often focused on classification tasks without incorporating a robust segmentation process, leading to suboptimal performance in identifying pneumonia-affected regions. Integrating advanced segmentation techniques with transfer learning, which leverages pre-trained models on large datasets, remains underexplored. This study addresses these gaps by applying transfer

learning to fine-tune pre-trained deep learning models (DeepLabV3, SegNet, and U-Net) for pneumonia segmentation in chest X-rays. By doing so, we seek to enhance segmentation accuracy, reduce the need for extensive annotated datasets, and improve the reliability of pneumonia diagnosis in clinical settings.

2.2 DeepLabV3

DeepLabV3 is introduced to the segmentation of semantic segmentation jobs[5], which mainly performs the pixel-level classification, in which pixel placement to preconfigured class is done by achieving a detailed understanding of traditional bounding boxes. It includes a MobileNetV2 or Xception-based feature extractor backbone for catching hierarchical features through input images. Its innovations are atrous (dilated) convolutions. Its design is shown at Figure 1.

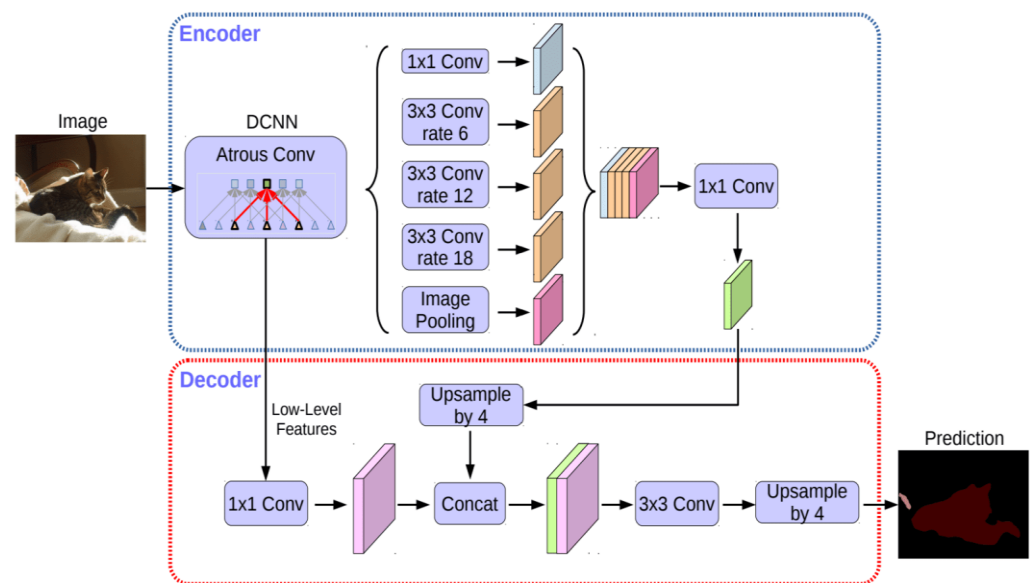


Figure 1. The Architecture of DeepLabV3[20]

The increment of the concerned field with no parameter increment is done by its convolutions that aid the efficient capturing of contextual information. The critical thing is that the Atrous Spatial Pyramid Pooling (ASPP) module employs various dilation-rated parallel atrous convolutions that efficiently capture contextual information with many scales. This strategy can improve the prediction at various scales, with accurate and exact semantic segmentation occurring.

2.3. U-Net

U-Net was introduced in 2015 to segment semantic jobs in medical imaging analysis [7], which is constituted by unique features, including an encoder for catching context and performing feature extraction. Its design is described in Figure 2. It consists of convolution layers, with max-pooling for eliminating spatial dimensions. The bottleneck layer is the transition point for keeping high-level abstract features and eliminating spatial dimensions. The decoder does the upsampling of feature maps to restore the spatial resolution. It mirrors the encoder with upsampling employing deconvolutions with concatenation of respective feature maps through the path of contraction. It can perform detailed information recovery gradually. Its innovative feature, skip connections, and maps of features through the encoder are linked to respective maps at the decoder, serving fine-grained upsampling. The final layer contains a convolutional layer by sigmoid activation operation, providing a possible map for binary segmentation jobs.

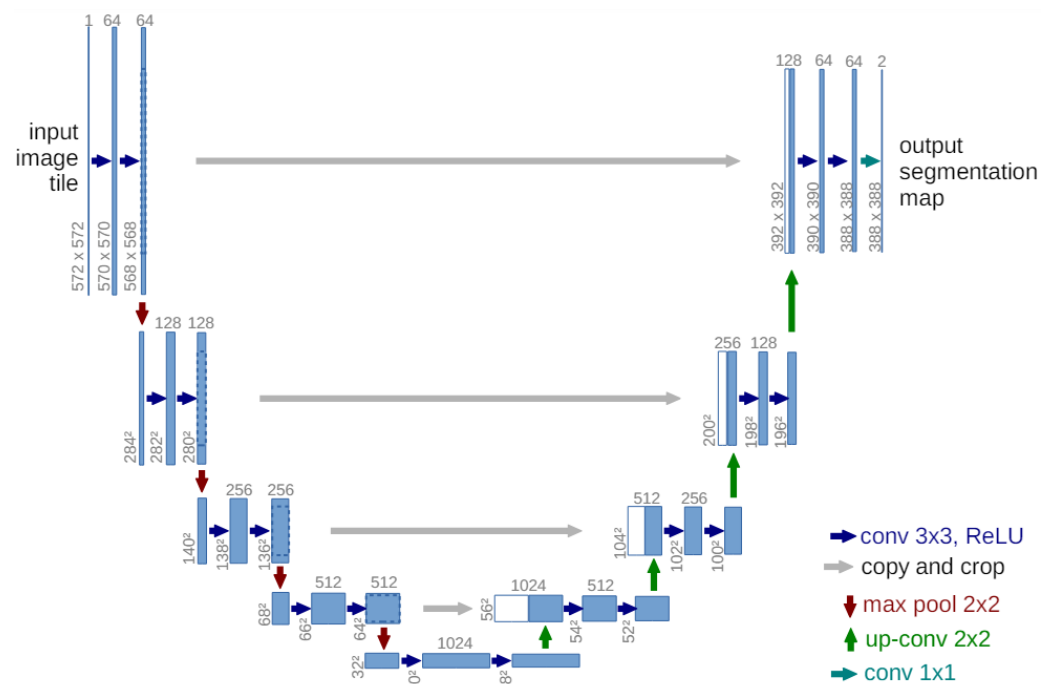


Figure 2. The Architecture of U-Net[7]

2.4. SegNet

The semantic segmentation network (SegNet) introduces the segmentation of semantic jobs. It is applied to real-time applications, including robotics and autonomous vehicles, for which the segmentation of exact and effective pixel-level is crucial. It deploys CNN to the operation of decoding and encoding, where the encoder extracts hierarchical features at the input image with various convolution layers to eliminate spatial dimensions. The decoder reorganizes segmented output with the generated features of an encoder. It is presented in Figure 3.

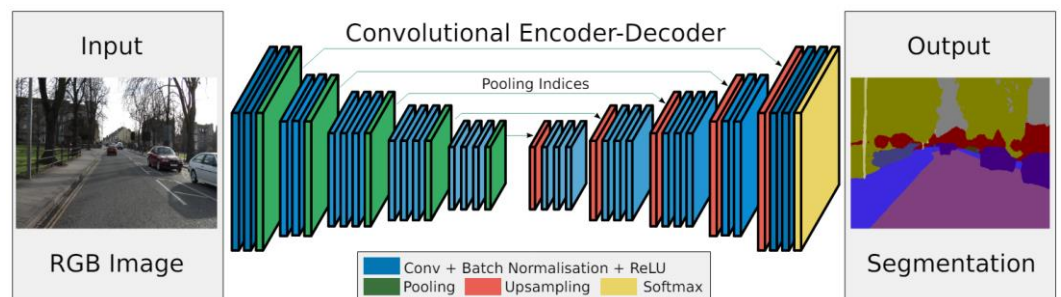


Figure 3. The Architecture of SegNet[6]

Upsampling in low-resolution feature maps is done to match the original resolution by employing the upsampling of max-pooling indices. It employs max-pooling indices caught at the pooling activity of the encoder, which maintains spatial information at the input image by pointing to maximum-valued locations at pooled regions. These indices place the correct value at original positions in upsampling by reconstituting the segmented portions. Moreover, it contains skip connections for the decoder and encoder to serve fine-grained operations and combine high-level and low-level features to enhance segmentation. Softmax operation is utilized at the final layer for possible pixel distribution by converting the output to a segmentation map, at which the pixel classification is done with cross-entropy loss operation.

3. Proposed Method

This system focuses on the development of a pneumonia segmentation system utilizing deep learning models, namely UNet, SegNet, and DeepLabv3, applied to a chest X-ray images

dataset sourced from the Kermany dataset [21], [22], obtained from the Guangzhou Women and Children's Medical Center. The dataset encompasses 5232 chest X-ray images, including normal and pneumonia-afflicted conditions. The methodology begins with polyline annotation using LabelMe tools, followed by converting JSON file annotations to Mask images. The dataset is then split into a training set (75%) and a validation set (25%). Preprocessing steps include converting input images from RGB to BGR color space, resizing the images to 256×256 dimensions, and normalizing pixel intensity in both RGB and Mask images. Subsequently, the training and testing datasets are loaded, and the data is converted to a tensor format for the training process. The segmentation model is trained, and the trained model is evaluated. The system utilizes a flowchart, described in Figure 4, to illustrate the sequential steps of the training process. The model achieving the desired accuracy is saved for future use. This systematic approach ensures the effective utilization of deep learning models for pneumonia segmentation in chest X-ray images, with a clear outline of the entire process from data preparation to model evaluation and saving.

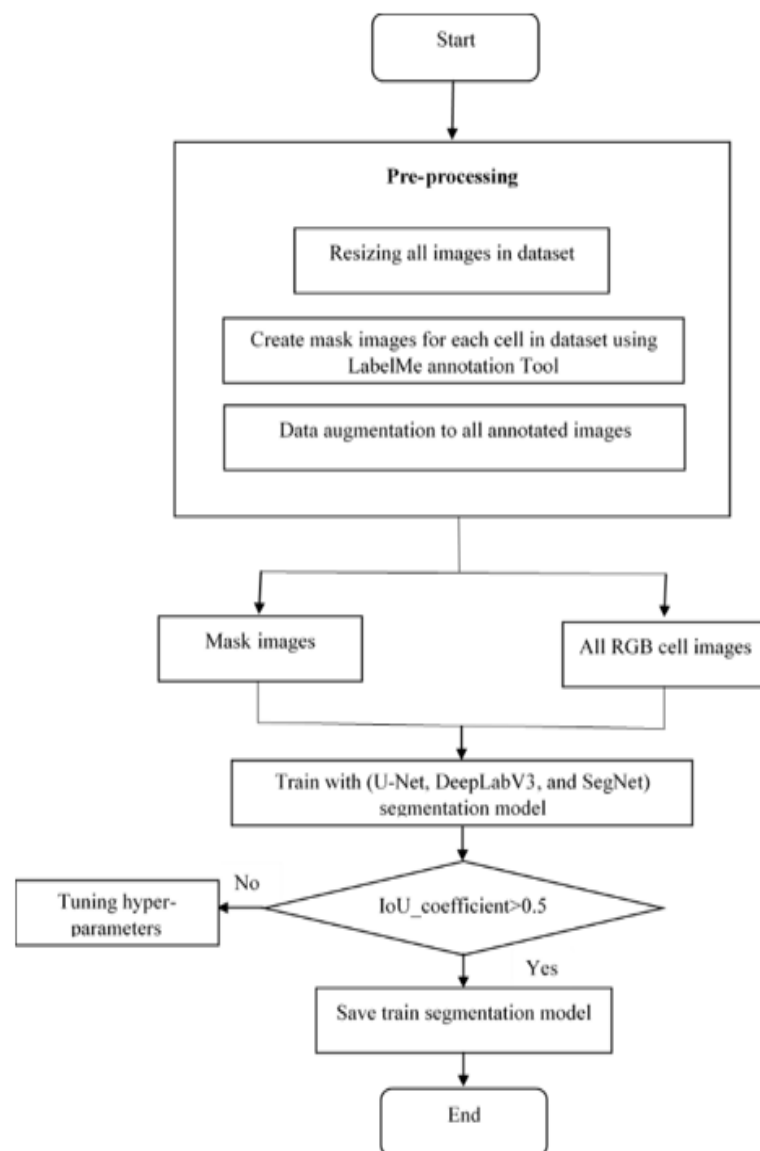


Figure 4. Flowchart of Training

During the testing phase, the input image undergoes an initial resizing at the pre-processing stage. Following this, the trained model is loaded, and the resizing is performed. If the pneumonia segment is detected, the created pneumonia binary cell segment is done. The testing process is depicted in Figure 5, illustrating the step-by-step flow of operations involved in resizing, prediction, and output generation during the testing phase of the pneumonia

segmentation system. This clear and concise description outlines the essential steps taken to evaluate the model's performance on new or unseen data, highlighting the pivotal role of resizing and prediction in producing the final pneumonia segment binary cell image.

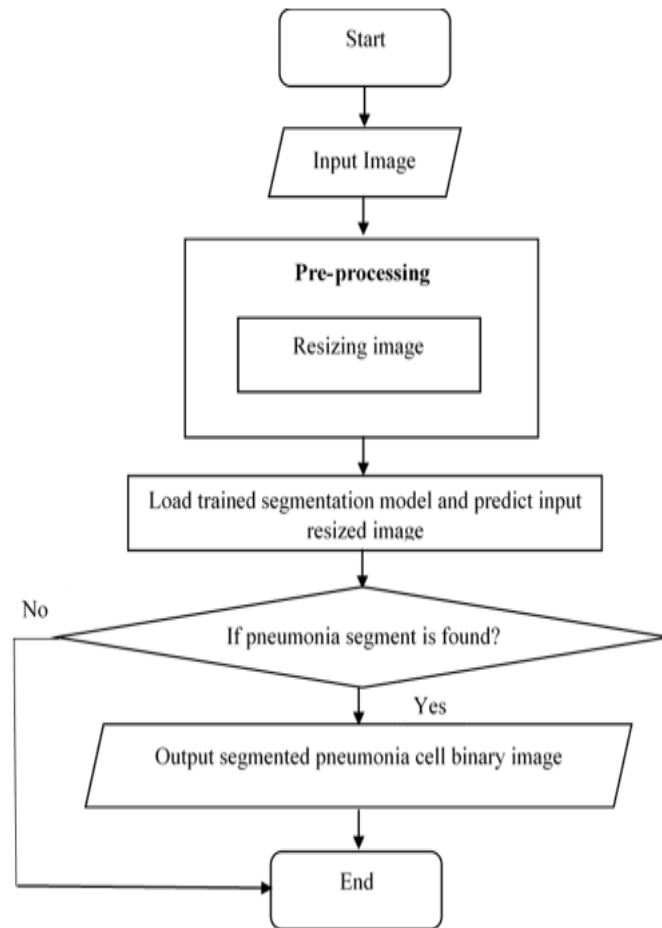


Figure 5. Flowchart of Testing

The assessment of evaluation criteria aims to provide comprehensive insights into the performance metrics, with a particular emphasis on key parameters like the Intersection over Union (IoU) coefficient and accuracy. The primary objective of this evaluation is to assess the effectiveness of the deep learning segmentation model utilized in the study, ensuring a nuanced understanding of its performance across different criteria. Using diverse indicators allows for a multifaceted assessment, providing a robust and comprehensive evaluation of the segmentation model's capabilities.

4. Results and Discussion

The Kermany Chest X-ray dataset, which includes pneumonia and normal conditions, is utilized as this system's foundational dataset. 75% for training and 25% for testing is split. Evaluation criteria, the Intersection over Union (IoU) coefficient, and accuracy are assessed for the system to ensure robust classification capabilities into pneumonia and normal conditions accurately. Different segmentation models employ distinct loss functions in this system's context. SegNet utilizes binary cross-entropy loss, a commonly employed loss function in binary classification tasks.

On the other hand, the unet3p_hybrid_loss function is employed by DeepLabV3 and U-Net. Jaccard loss, Focal loss, and SSIM loss (Structural Similarity Index) are combined to form this unet3p_hybrid_loss function. The choice of this hybrid loss function reflects a comprehensive approach to optimizing model training, incorporating diverse elements to enhance the overall segmentation performance. Each loss function is tailored to the specific

requirements and objectives of the respective segmentation models, contributing to a nuanced and effective training process. Equation (1) is used to calculate Jaccard loss.

$$\text{Jaccard loss} = J(A, B) = \frac{|A \cap B|}{|A \cup B|} \quad (1)$$

SSIM loss is depicted by Equation (2).

$$\text{SSIM}(x, y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \quad (2)$$

Where x and y are the two images. μ_x and μ_y are the mean values, σ_x and σ_y are the variance values, σ_{xy} is the covariance; c_1 and c_2 are constants. Focal loss is described by Equation (3).

$$\text{Focal Loss} = - \sum_{i=1}^n (i - p_i)^\gamma \log_b(p_i) \quad (3)$$

Where γ is the tuning parameter, p_i is the predicted probability. Binary Cross Entropy Loss is described by Equation (4).

$$L = - \frac{1}{N} \sum_{i=1}^N y_i \cdot \log(p(y_i)) + (1 - y_i) \cdot \log(1 - p(y_i)) \quad (4)$$

where y_i represents the actual class and $\log(p(y_i))$ is the probability of that class; $p(y_i)$ is the probability of one, and $1 - p(y_i)$ is the probability of zero. Figure 6 shows the segmented images of U-Net. Figure 7 describes the segmented images of DeepLabV3. Figure 8 presents the segmented images of SegNet.

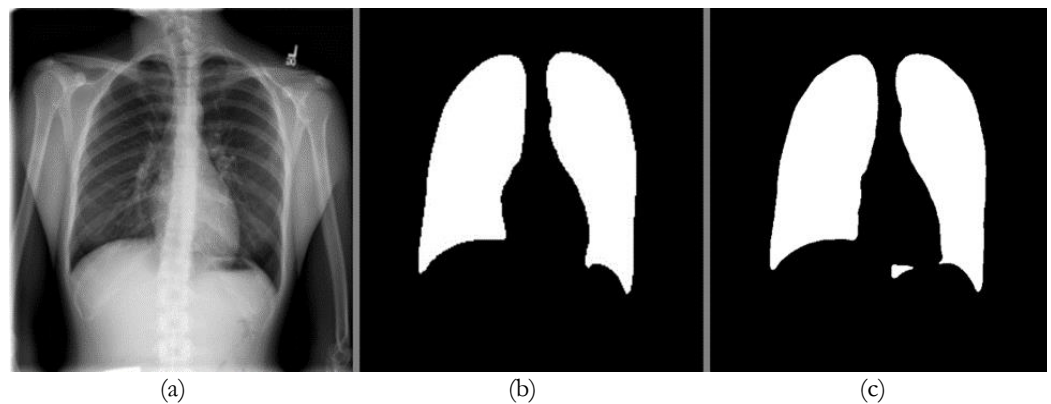


Figure 6. Sample segmented images of U-Net (a) Input Image; (b) Predicted masks; (c) Overlay masks.

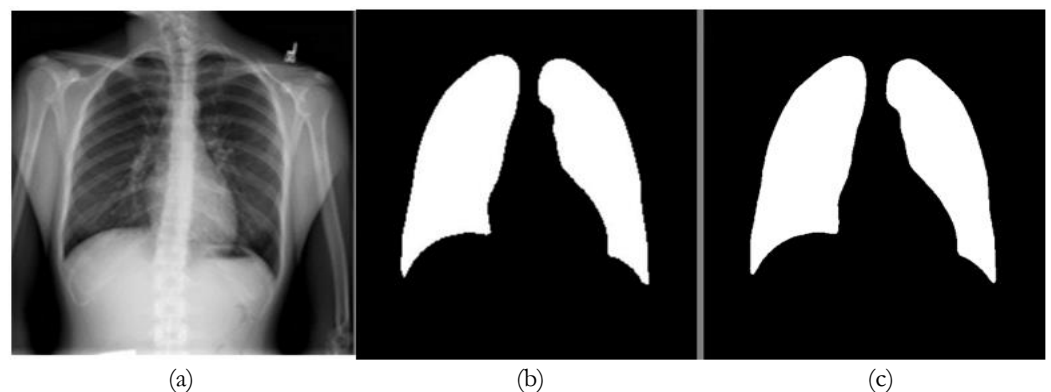


Figure 7. Sample segmented images of DeepLabV3 (a) Input Image; (b) Predicted masks; (c) Overlay masks.

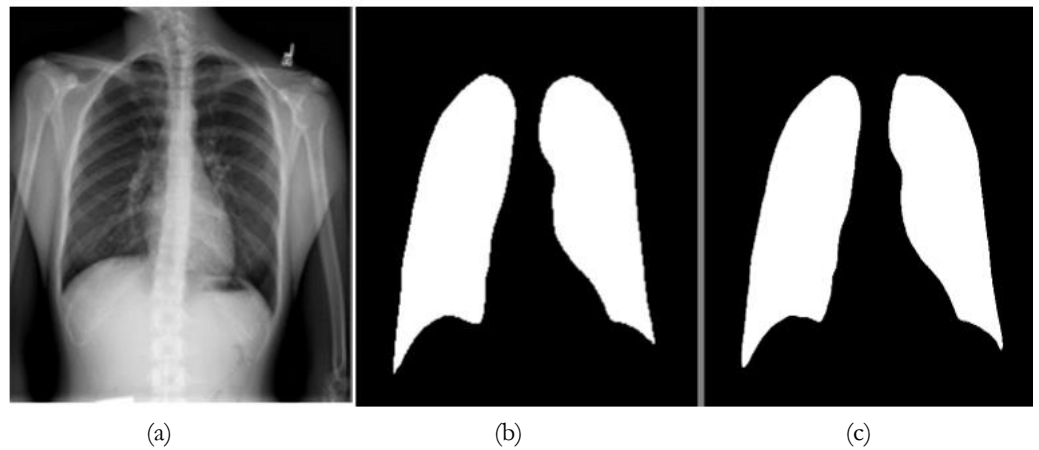


Figure 8. Sample segmented images of SegNet (a) Input Image; (b) Predicted masks; (c) Overlay masks.

Table 1 describes the parameters of three models. Figure 9 describes the performance of three models. Figure 10 describes the IoU results of three models.

Table 1. Parameters settings of three models.

Parameter	SegNet	DeepLabV3	U-net
Encoder	5 Convolutional layers with max-pooling	Backbone network: ResNet with atrous convolutions	5 Convolutional layers with max-pooling
Decoder	Mirrors encoder architecture with upsampling	Decoder	Mirrors encoder architecture with upsampling
Activation function	ReLU	ReLU	ReLU
Loss function	Binary Cross Entropy	UNET3p_hybrid_loss	UNET3p_hybrid_loss
Optimizer	Adam	Adam	Adam
Learning rate	0.01	0.01	0.0001
Atrous Spatial	None	Atrous Spatial Pyramid Pooling (ASPP)	Atrous Spatial Pyramid Pooling (ASPP)
Dropout	0.5	0.5	0.5
Batch size	8	8	8

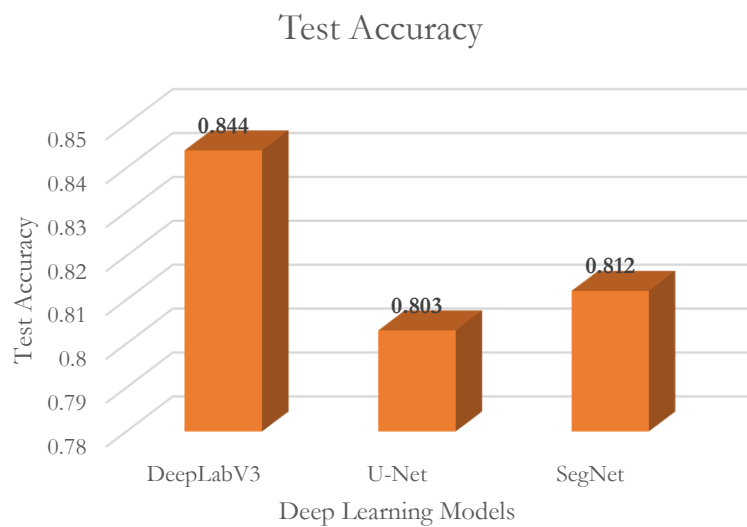


Figure 9. Accuracy results of three models.

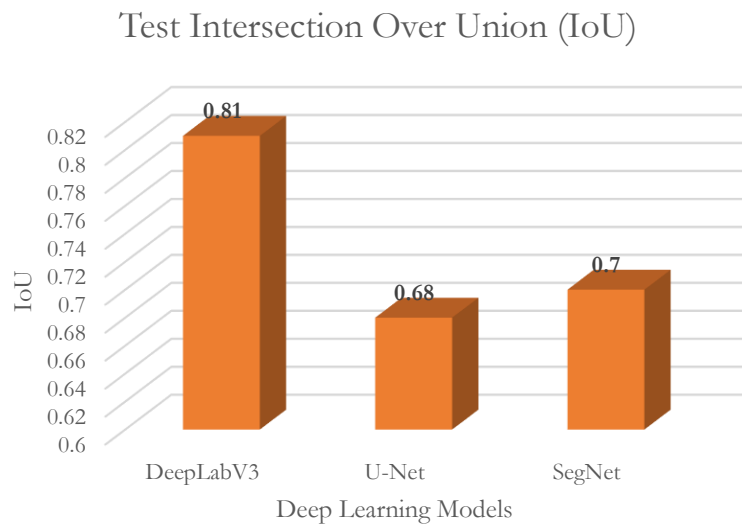


Figure 10. IoU results of three models.

This study evaluated the segmentation performance of three state-of-the-art models, DeepLabV3, U-Net, and SegNet, focusing on test accuracy and Intersection over Union (IoU) results. DeepLabV3 exhibited superior test accuracy compared to both U-Net and SegNet. Through rigorous evaluation on a separate test dataset, DeepLabV3 consistently achieved higher accuracy scores, indicating its proficiency in accurately segmenting pneumonia regions from medical images. The robustness of DeepLabV3 across different subsets of the test data highlights its reliability and effectiveness in real-world applications. Intersection over Union (IoU) is a key metric for evaluating the spatial overlap between predicted and ground truth segmentation masks. DeepLabV3 demonstrated significantly higher IoU scores compared to U-Net and SegNet. The increased IoU values indicate that DeepLabV3 generated segmentation masks more closely aligned with the ground truth annotations, capturing pneumonia regions with greater precision and completeness. The robust segmentation performance of DeepLabV3 underscores its potential for enhancing diagnostic accuracy and clinical decision-making in pneumonia diagnosis and treatment. The superior performance of DeepLabV3 can be attributed to its advanced architecture, which incorporates atrous spatial pyramid pooling (ASPP) and dilated convolutions to capture multi-scale contextual information effectively. By leveraging rich contextual cues and global dependencies, DeepLabV3 achieves more accurate and comprehensive segmentation of pneumonia regions, surpassing the capabilities of U-Net and SegNet.

5. Conclusions

Pneumonia occurs as a major health issue in developing and underdeveloped regions in which poor living conditions and overcrowding are common, and high levels of pollution with inadequate medical infrastructure are formed. This study focuses on accurate pneumonia classification with U-Net, SegNet, and DeepLabV3 employing the Kermay dataset. Experimental results show that the segmentation system achieves an accuracy of 0.844 with DeepLabV3, 0.803 with U-Net, and 0.81 with SegNet. Additionally, the Intersection over Union (IoU) values are 0.81 for DeepLabV3, 0.68 for U-Net, and 0.70 for SegNet. These findings demonstrate that the system, particularly with DeepLabV3, surpasses U-Net and SegNet in pneumonia segmentation. Future work aims to enhance the system by exploring an ensemble model that integrates multiple deep learning approaches for pneumonia segmentation, with the goal of further improving the accuracy and robustness of the segmentation system in medical image analysis.

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