Optimizing Lung Segmentation In Chest X-Rays Through Comparative Preprocessing And Deep Learning Benchmarks

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Abstract

This paper introduce a complete optimization process for lung segmentation in chest xrays (cxr) – a necessary step for a number of computer-assisted diagnoses, most notably tb and thoracic diseases. Here we compared two types of deep learning models to determine which type is better suited for cxr lung segmentation. We evaluated both a standard dense encoder-decoder network (with no attention mechanism) and a dense encoder-decoder network with an attention mechanism. Additionally, we studied nine different image enhancement approaches and found that a specific combination of preprocessing steps improved the performance of the deep neural networks. The nine preprocessing approaches included a variety of traditional histogram equalization techniques as well as hybrid approaches using the balance contrast enhancement technique (bcet) and discrete wavelet transform (dwt) to analyze the effectiveness of each approach, the we developed a total of six model configurations including a densenet201 unet model and an adaptive segunet model from existing papers. A thorough quantitative analysis of each model's performance utilized the intersection over union (iou), dice coefficient, and hausdorff distance metrics. Overall, we demonstrated that the use of a hybrid preprocessing approach (bcet+dwt) provides a significant increase in performance of deep encoder models by reaching a training dice coefficient of 0.9344 while also demonstrating that overly aggressive wavelet denoising negatively impacts attention-based models by eliminating vital textural information; this research demonstrates that a preprocessing stage optimized for cxr imaging combined with a back-end architecture utilizing densely interconnected layers is superior to attention-only models for general lung segmentation applications and provides a cost-effective alternative.

Keywords: Chest X-Ray, Image Preprocessing, Lung Segmentation, Deep Learning, Benchmark Analysis.

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1. Introduction

Thoracic pathologies remain the most common use of Chest Radiography (CXR) due to its ability to be acquired rapidly and at minimal cost [1]. With an increased demand for imaging, particularly due to the recent upsurge in global infectious diseases such as Tuberculosis [2] it is becoming increasingly difficult for radiologists to interpret images due to a large volume of imaging being performed daily. Due to this, researchers have developed Automated Computer-Aided Diagnosis (CAD) systems to aid in the radiologist's workload [3]. Regardless of what CAD system is implemented, segmenting the pulmonary parenchyma will always be a crucial step in the process of identifying Regions of Interest (ROI) and intensity normalization [4]. Deep learning models have become increasingly popular; however, they still struggle to provide consistent segmentation results within different clinical environments and/or on different scanners [6,1].

A primary reason that CXR analysis remains so challenging is due to the complexity of the radiographic projection itself. Low contrast levels exist in both the retrocardiac and subdiaphragmatic areas of the chest radiograph. These areas of low contrast lead to ambiguous boundaries [7]. To combat this problem many researchers have utilized traditional preprocessing methods, such as Histogram Equalization (HE) and Contrast Limited Adaptive Histogram Equalization (CLAHE) to improve the clarity of the radiographs [8]. While HE and CLAHE are able to enhance the radiographs visually, they also amplify noise and saturate the intensities of the images. Both noise amplification and intensity saturation can negatively affect the distribution of features for Convolutional Neural Networks (CNNs) [5]. More recent studies suggest that using hybrid preprocessing pipelines, combining intensity normalization with frequency-domain denoising may allow for better consistency in segmentation results. In particular, previous studies have suggested that utilizing wavelet based filtering to highlight structural boundaries prior to processing the image through a CNN may result in improved model convergence [9, 10].

Parallel to advancements in preprocessing methods, the architecture of segmentation networks has evolved from the standard UNet to include more dense and interconnected frameworks [11]. Incorporating encoders, such as DenseNet into segmentation models allows for greater feature reuse, and enables models to identify semantic detail and relationships in images using fewer parameters [4]. Additionally, in recent years, the field of computer vision has transitioned to focus on developing models that incorporate attention mechanisms. Attention mechanisms employ self-attention modulesto enable the dynamic weighing of the importance of spatial features in the segmentation of medical images [12, 13]. Attention mechanisms are theoretically superior to suppress background noise in the complex and noisy nature of medical images [14, 15]. There currently exists a research gap at the intersection of aggressive preprocessing and attention-based modeling. Many current state of the-art segmentation methodologies consider preprocessing and model architecture to be independent variables, and assume that cleaner images universally benefit all network types [16, 17]. This assumption fails to account for a potential trade-off: attention mechanisms rely on high frequency textural signals to compute their weighting coefficients. Aggressive denoising techniques, such as Discrete Wavelet Transform (DWT), while effective at eliminating quantum mottle, may unintentionally remove textural dependencies necessary for the attention mechanism to function properly, resulting in performance degradation in attention-guided networks [10, 14].

This study addresses the previously identified gap by performing a systematic evaluation of lung segmentation pipelines, examining the compatibility of nine preprocessing methods and six deep learning architectures. Specifically, this study investigates the utility of the Balance Contrast Enhancement Technique (BCET) when used in conjunction with DWT, testing the hypothesis that deep, densely connected encoders (DenseNet201 U-Net proposed in paper[4])are less affected by the removal of textural information compared to attention-based architectures (Adaptive SegUNet proposed in paper [14]). This study provides empirical evidence to optimize the segmentation pipeline in resource-constrained, high variability clinical environments [3].

2. Methodology

To conduct a thorough evaluation of the segmentation pipeline, our research utilizes a systematic three-stage approach. Stage one is based on the creation of a multisource composite data base, simulating domain changes that occur in real world applications. Stage two consists of comparative preprocessing and benchmarking of enhancements using a traditional method, and the hybrid model. Stage three includes configuring and training two different deep learning architectures, the DenseNet201 U-Net from paper [4], and the Adaptive SegUNet from paper [14]; both are designed to compare the use of reused features with attention mechanisms.

2.1 Dataset Composition and Characteristics

In order to ensure that the hybrid models are statistical valid and capable of generalized application, a composite data base was created consisting of images from four different 4 data bases. The MC (Montgomery County) data base and the SH (Shenzhen Hospital) data base provided the primary training distribution; these data bases contained a combination of images of healthy lungs and images of various pathologies (i.e., consolidations and effusions), which are necessary for developing robust feature learning. In addition, to create additional variability in the data base, the JSRT (Japanese Society of Radiological Technology) data base was added and contributed images at moderate resolution and gold-standard masks for detecting nodules. A data base of images from a Private Hospital was used exclusively as an external test set to evaluate the real-world robustness and clinical applicability of the hybrid models.

A total of 1,075 images were in the data base, and it was divided into an 80/20 ratio for training/validation splits. Standardization of image processing involved converting the original DICOM/PNG files into 3-channel RGB tensors and resizing the images to a consistent dimension of 224 x 224 pixels in order to satisfy the input requirements of the pre-trained backbone.

This section presents an overview of our work concerning the processing of the input signals. Our research is primarily concerned with improving the quality of chest x-ray images that are typically of low contrast in the retrocardiac region as well as have high levels of quantum noise. This can cause convolutional networks to perform poorly.

2.2 Design of the Preprocessing Benchmark

We developed a comparative design for the preprocessing benchmark that would allow us to evaluate the most effective method for enhancing the input signal. Our original bench-mark contained nine different methods of preprocessing; these included: Traditional Histogram Equalization (HE); Contrast-Limited Adaptive Histogram Equalization (CLAHE); Gamma-Correction and HybridFilters (e.g., CLAHE+Median) [21], [8]. After conducting preliminary quantitative evaluations of Peak-Signal-to-Noise-Ratio (PSNR) and Structural-Similarity-Index (SSIM), we developed a hybrid pipeline using the Balance Contrast Enhancement Technique (BCET) and Discrete-WaveletTransform (DWT) as they had better preserved anatomical structures than did the more aggressive spatial-filtering techniques used in previous studies [16].

Balance Contrast Enhancement Technique (BCET) The Balance Contrast Enhancement Technique (BCET) was chosen for the purpose of normalizing the intensity of the image. As opposed to standard histogram equalization, which has been shown to introduce saturation artifacts, BCET employs a parabolic transformation function to stretch the pixel intensity range based on the image's minimum, maximum, and mean values [9]. This dynamic adjustment of the coefficients of the parabolic function allows it to compensate for differences in exposure settings between images (i.e., under- or overpenetrated images) by setting a target mean brightness for the image while preserving the local information entropy required for detecting diseases [5].

Discrete Wavelet Transform (DWT) Following the application of BCET to correct for variations in intensity, we applied Discrete Wavelet Transform (DWT) for targeted denoising. Using the bior1.3 wavelet basis, we decompose the image into four bands: the approximation (LL) band contains the structural information; and the three detail bands (LH, HL, HH) contain highfrequency edges and noise [10]. We applied soft-thresholding to the detail bands. Softthresholding is an effective way to reduce the number of small coefficients that correspond to Poisson noise to zero, while also shrinking larger coefficients to prevent "ringing" artifacts caused by the "Gibbs Phenomenon" [16]. The final denoised image is then reconstructed through the inverse discrete wavelet transform (IDWT).

2.3 Deep Learning Architectures and Implementation

We will now review how we used deep neural networks to evaluate whether our optimized preprocessing steps could improve lung segmentation performance.

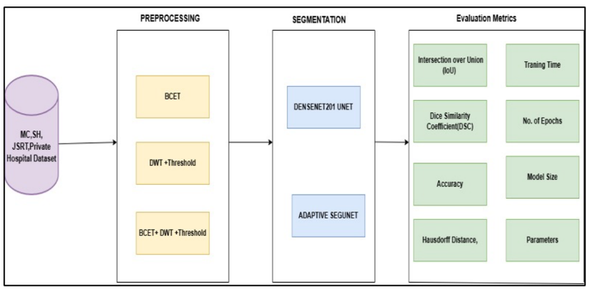


Figure 1: Schematic illustration of our preprocessing, segmentation, and evaluation workflow for CXR lung segmentation

DenseNet201 U-Net

Our first segmentation model uses Transfer Learning to leverage dense connectivity in an encoder. Each layer in the encoder is connected to every previous layer;

there are L(L+1)/2 total connections. By optimizing dense connectivity we ensure optimal flow of information through the network. Thus we can detect subtle variations in features without needing as many parameters as other models (ResNet backbones). For the bottleneck we use Dilated Convolutional Layers to expand the receptive field of the network, and we design a custom decoder using residual blocks to keep gradients stable during the reconstruction of fine spatial details [4].

Adaptive SegUNet

Our second segmentation model is the Adaptive SegUNet which uses "AttentionGuided" learning. In place of the usual Skip Connections, the Adaptive SegUNet uses Attention Gates (AGs) that use a gate signal to selectively weight the importance of the features provided by the encoder [14]. We hypothesize that when textural cues are eliminated from images by aggressive preprocessing, the use of AGs may cause the model to lose its ability to selectively focus on important areas (the lungs) and instead attend to irrelevant areas (background). This will allow us to test the hypothesis that attention mechanisms have limitations when textural cues are reduced [7].

Training Protocol

Both models were implemented using TensorFlow/Keras with GPU support. To train both models, we used the Adam Optimizer with a learning rate of 1e-4 and a batch size of 8 over 30 Epochs. We used Dice Loss as our objective function to deal with the class imbalance problem between the lungs and the background. We also used real time data augmentation consisting of rotation (±15º) and zooming (±10º) to increase model robustness.

3. Results

Visual representations of the results of random samples of chest X-rays and the respective enhanced output produced using the different preprocessing pipelines can be found in Figure 2. Our approach has been thoroughly tested and analyzed through extensive computations and demonstrated that the numerous hybrid preprocessing pipelines we have used for medical image analysis are effective. To evaluate the quality of both the preprocessing stage and the segmentation stage of our approach, we have employed several evaluation metrics including Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), Dice Coefficient, and Hausdorff Distance.

3.1 Preprocessing and Image Quality Evaluation

In order to identify the optimal input for the deep learning models, an analytical study was performed to compare the performance of each of the 9 individual and combined preprocessing enhancement techniques on the basis of several criteria.

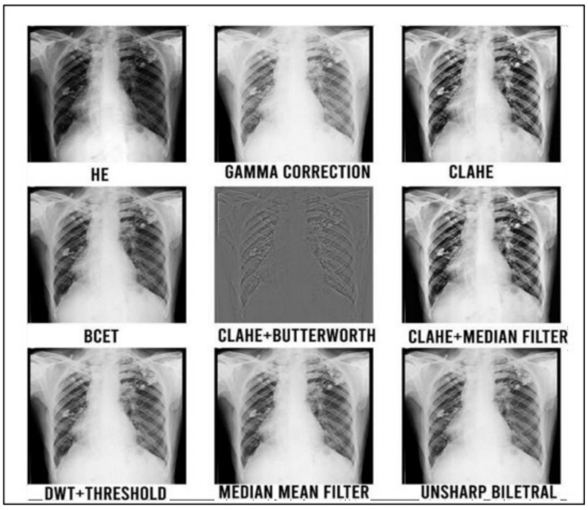
Table 1: Analytical Study Comparing Performance of Different Preprocessing Methods (Evaluation Metrics)

Preprocessing Technique	**PSNR (dB)**	**SSIM**	**Entropy**	**RMS Contrast**	**Mean Intensity**
Original (Baseline)	—	1.00	7.10	81.30	131.40
Histogram Equalization (HE)	18.3	0.88	6.90	82.35	108.23
CLAHE	23.5	0.82	7.20	81.33	129.50
Gamma Correction	22.5	0.97	6.80	82.22	147.42
BCET	**39.1**	**0.99**	7.10	80.70	128.90
CLAHE + Butterworth	5.34	0.19	6.06	28.47	24.96
CLAHE + Median	23.38	0.76	7.23	81.09	129.52
DWT + Threshold	**40.77**	**0.96**	7.09	81.11	130.99
Unsharp + Bilateral	34.83	0.87	7.12	81.47	131.52

As illustrated in Table 1, BCET is superior to the traditional techniques such as Histogram Equalization (HE) and CLAHE. BCET exhibited the best values of SSIM (0.99) and PSNR (39.1 dB). These values indicate that BCET improves the contrast while maintaining the original histogram shape, which is critical for preserving anatomical integrity.

Moreover, the combination of DWT and soft thresholding significantly reduces quantum noise. Among all denoising methods, "DWT + Threshold" configuration exhibits the highest PSNR (40.77 dB). On the other hand, aggressive spatial filtering configurations such as "CLAHE + Butterworth", severely degrade structural detail (SSIM = 0.19), confirming they are not suitable for this application.

When visually compared (see Figure 2), the enhanced images using BCET exhibit balanced illumination and lack saturation artifacts found in HE. The processed images using DWT exhibit improved sharpness and are able to isolate rib edges from the lung parenchyma without the blur caused by the Gaussian filter.



Original Xray

Figure 2: Original Xray & Enhanced Outputs(HE, CLAHE, Gamma, BCET, CLAHE + Median, CLAHE + Butterworth, Mean–Median,Unsharp + Bilateral, DWT + Threshold)

3.2 Segmentation Model Evaluation

An evaluation of the DenseNet201 U-Net and Adaptive SegUNet was performed using several different preprocessing techniques to compare how each model performs in different environments.

3.3 Benchmarking Quantitatively

The study shows that the DenseNet201 U-net in combination with the BCET+DWT preprocessing pipeline yielded the highest performance across all metrics. Specifically, it produced a Training Dice coefficient of 0.9344 and an Intersection-over-Union (IoU) of 0.8778. What is most notable is that it had the lowest Hausdorff distance (14.93), which indicates that the model's boundaries were closest to the actual boundaries. Since the Hausdorff distance is used as a measure of how well a boundary matches another boundary (in this case the actual boundary), the lower the value, the better the model's boundary adheres to the actual boundary. Therefore, since the DenseNet201 U-Net produced the smallest Hausdorff distance, it produced the best boundary for clinical use. In contrast, the Adaptive SegUNet consistently outperformed the DenseNet model. Although the SegUNet performed relatively well on the original images, its 9 performance significantly decreased when the same images were denoised using DWT and thresholding. It then produced a Dice score of 0.7990. This decrease in performance demonstrates that the DenseNet encoder benefits from the removal of noise (as demonstrated by a 9.3% improvement). On the other hand, the attention mechanisms within the SegUNet likely struggle to remove the high frequency textural signal that they utilize for gated feature extraction.

Table 2: Overall Segmentation Evaluation (Training/Test Metrics)

Sr no	Configuration	Train Dice	Train IoU	Test Dice	Test IoU	Hausdorff Dist.
1	DWT+ Threshold + DenseNet201 Unet	0.9294	0.8691	0.8395	0.7305	20.58
2	BCET+ DenseNet201 Unet	0.8405	0.7312	0.8062	0.6811	26.23
3	BCET+DWT+ Threshold+DenseNet201 Unet	**0.9344**	**0.8778**	**0.8521**	**0.7460**	**14.93**
4	DWT+Threshold+Adaptive SegUNet	0.8092	0.6796	0.7781	0.6369	31.61
5	BCET + Adaptive SegUNet	0.8099	0.6806	0.7673	0.6224	30.49
6	BCET+DWT+ Threshold +Adaptive SegUnet	0.7990	0.6653	0.7452	0.5939	36.96

Figure 1: Original X-ray and corresponding ground truth mask

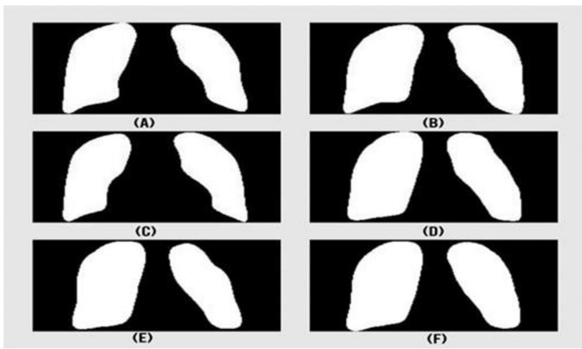


Figure 2: Predicted segmentation mask created by

each model. A) DWT + Threshold + DensessNet201 U-Net B) BCET + DenseNet201 U-Net C) BCET + DWT + Threshold + DenseNet201 U-Net D) DWT + Threshold + Adaptive SegUNet E) BCET + Adaptive SegUNet F) BCET + DWT + Threshold + Adaptive SegUnet

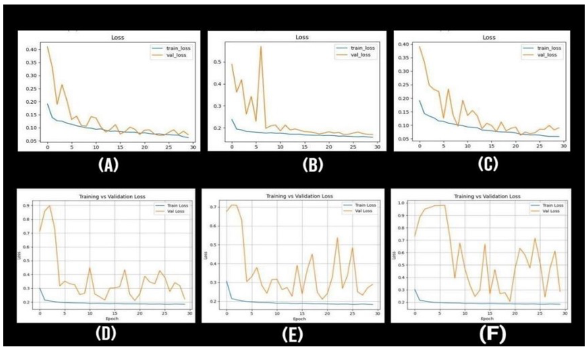


Figure 3: Training vs validation loss for each model. A) DWT + Threshold + DenseNet201 U-Net B) BCET + DenseNet201 U-Net C) BCET + DWT + Threshold + DenseNet201 U-Net
D) DWT + Threshold + Adaptive SegUNet E) BCET + Adaptive SegUNet F) BCET + DWT + Threshold + Adaptive SegUNet

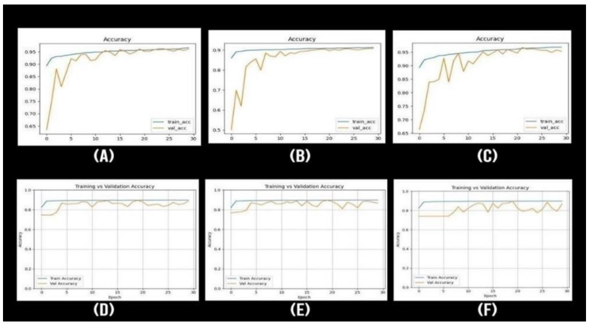


Figure 4: Training vs validation accuracy for each model. A) DWT + Threshold + DenseNet201 U-Net B) BCET + DenseNet201 U-Net C) BCET + DWT + Threshold + DenseNet201 U-Net D) DWT + Threshold + Adaptive SegUNet E) BCET + Adaptive SegUNet F) BCET + DWT + Threshold + Adaptive SegUNet

Vision and Stability Evaluation

The segmentation masks produced by the models are shown in Figure 4. The segmentation masks produced by the DenseNet201 U-Nets (A, B & C) closely match the true segmentation masks and have accurately captured the costophrenic angles. However, the segmentation masks produced by the Adaptive SegUNet (D, E & F) have been smoothed excessively and do not always produce accurate segmentation of the lung apices.

Analysis of the training stability in Figure 5 has also shown that the loss curves for the DenseNet model have steep and consistent decreases. These results indicate stable and successful learning dynamics for the DenseNet model. In contrast, the SegUNet loss curves are unstable and have begun to plateau early, supporting the hypothesis that dense connection-based encoders are more suitable for tasks such as image segmentation in medical imaging than solely attentionbased encoders, especially when working with preprocessed images from radiography.

4. Discussion

This investigation has demonstrated the relative merits of the adaptive segunet and the densenet201 U-net models in comparison to each other, with respect to lung segmentation for the purposes of TB diagnostics. The densenet201 U-net was found to be the most effective of the two models due to its higher dice coefficient (0.9344) and lower hausdorff distance (14.93) values; this is indicative of the ability of the model to accurately delineate the anatomical boundaries of the lungs, which are necessary for clinical assessments such as cardiothoracic ratios. The authors believe that the reason for the success of the densenet backbone is the reuse of features at multiple scales and the use of a custom residual decoder to effectively separate the lung parenchyma from the surrounding rib texture, even after the application of aggressive denoising algorithms.

In contrast, although the hybrid BCET+DWT pipeline provided the dense encoder with a reduction in quantum noise, it appeared to be a source of adversarial perturbations to the Adaptive SegUNet. This may indicate that the weighting coefficients calculated by the attention gates rely heavily on the high frequency textural signals that are often interpreted as noise, therefore, the excessive smoothing that is applied during training can potentially result in the removal of important boundary information [14, 7, 16]. The results of this study provide further evidence of the trade-off that exists between the signal-to-noise ratio and the retention of textural semantic information that is required for attention-based learning. The clinical significance of the lower hausdorff distance of the densenet model indicates the greater accuracy of the model in defining the anatomical boundaries of the lungs, compared to the standard dice score method that may miss small but clinically significant errors [22].

5. Conclusion

Our study evaluated how well nine different image preprocessing methods can be combined with six different model architectures used in deep learning to perform chest xray segmentation. Our study found that the DenseNet201 U-Net had the highest accuracy of all the architectures we tested, with a Training Dice Coefficient of 0.9344 and a minimum Hausdorff Distance of 14.93. We believe the higher accuracy of the DenseNet201 U-Net compared to the other architectures is due to the fact that the DenseNet is a densely connected architecture that can reuse information from previous layers, and therefore produce more robust semantic representations of lung anatomy.

However, the effectiveness of preprocessing depends on the architecture being used. For example, the use of a hybrid Balance Contrast Enhancement Technique (BCET) and Discrete Wavelet Transform (DWT) proved effective at preparing images for the DenseNet encoder, but caused the Adaptive SegUNet to underperform. We believe this is because the wavelet transform removed some of the high frequency texture needed by the attention gate of the Adaptive SegUNet. Therefore, our study has shown that there is a trade-off between removing quantum noise and preserving high frequency textures when preprocessing images for use in segmentation models. Overall, our study shows that the combination of a deep, densely connected encoder with frequency-domain denoising is a state-of-the-art approach to perform binary lung segmentation. Additionally, our study suggests that purely attention-based approaches may not be the best solution for segmenting lungs in noisy radiographic environments.

Future studies could investigate the potential of using hybrid CNN-Transformer architectures (e.g., Swin-UNet) to improve the ability of segmentation models to recognize global patterns in the lungs. Another area for future investigation could be examining the effect of adversarial domain adaptation to improve the performance of segmentation models trained on one dataset to generalize to another dataset.

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