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Analysis of Various Types of Lung Image Segmentation Techniques

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Abstract— This paper presents a detailed study on lung image segmentation with special focus on the proposed **ResUNet++ framework**. Automated segmentation plays a key role in computer-aided diagnosis, as manual methods are often slow, subjective, and inconsistent. Traditional techniques struggle with low-contrast or irregular lung regions, whereas deep learning models such as U-Net, UNet++, ResUNet, Attention U-Net, PSPNet, DeepLabV3+, HRNet, and transformer-based networks have brought major improvements. Among these, our experiments show that ResUNet++ offers the best balance of **accuracy, stability, and efficiency**. It achieved the highest Dice, Precision, Recall, and IoU scores across datasets and showed strong adaptability to different domains. The ablation studies confirm that modules like squeeze-and-excitation and atrous spatial pyramid pooling play a vital role in handling complex pathologies. Visual results further support its ability to generate smooth and anatomically correct lung boundaries. Overall, ResUNet++ advances the state of the art in lung image segmentation and provides a reliable base for clinical tasks such as disease detection, lesion measurement, and treatment monitoring**.**

Keywords: CRX, CNN, U-Net, segmentation, Lung Image

I. Introduction

Lung disease segmentation plays a pivotal role in the diagnosis and treatment of various pulmonary conditions including pneumonia, tuberculosis, and COVID-19. Deep learning methods have revolutionized medical image segmentation, and among them, ResUNet++ stands out due to its ability to capture multi-scale contextual information, refine boundary details, and stabilize learning with residual connections. This documentation presents a comprehensive overview of the ResUNet++ architecture applied to lung disease segmentation, including methodology, architecture design, mathematical formulation, literature survey, and potential clinical applications. Lung diseases are among the leading causes of morbidity and mortality worldwide. Early detection and accurate diagnosis are crucial for effective treatment. Medical imaging modalities such as chest X-rays (CXR) and computed tomography (CT) scans are widely used to visualize lung structures and identify abnormalities. However, manual delineation of lung regions and pathological areas is time-consuming, error-prone, and subject to inter-observer variability. Therefore, automated lung segmentation has become an essential step in computer-aided diagnosis (CAD) systems. Traditional segmentation methods such as thresholding, active contour models, and region growing often fail in cases with low contrast or irregular disease patterns. Deep learning, particularly convolutional neural networks (CNNs), have emerged as powerful tools for medical image analysis. Architectures such as U-Net, UNet++, and their variants have demonstrated remarkable success in biomedical segmentation tasks. Among these, ResUNet++ integrates residual learning, squeeze-and-excitation (SE) blocks, and atrous spatial pyramid pooling (ASPP), making it highly effective for lung field and disease segmentation.

The method presented in [1] introduced the U-Net architecture, which quickly became the baseline for medical image segmentation. Its symmetric encoder-decoder design with skip connections allows for precise localization. However, it lacks robust multi-scale feature extraction. The study in [2] extended U-Net to 3D U-Net for volumetric medical data, enabling the segmentation of CT volumes. [3] introduced UNet++, which refined the skip connections with nested and dense pathways for better feature fusion. The technique in [4] proposed ResUNet++, adding residual units, SE blocks, and ASPP to address the limitations of U-Net and UNet++. The study in [5] presented Attention U-Net, incorporating attention gates to focus on relevant structures. DenseNet-based U-Nets, given in [6], improved feature reuse, while transformer-based models such as TransUNet in [7]

achieved superior results by capturing long-range dependencies. Recent works proposed in [8] and [9] applied deep learning for COVID-19 lung infection segmentation, while the methods given in [10] and [11] provided a benchmark study showing that deep learning outperforms conventional methods. Hybrid CNN-transformer approaches presented in [12] and [13] have further improved the segmentation of complex lung pathologies.

II. Foundations and Advances in Medical Image Segmentation

A. U-Net

A milestone in biomedical imaging, U-Net [1] introduced a symmetric encoder–decoder architecture with skip connections between matching layers. This structure preserves spatial context while enabling deep feature extraction, making it highly effective for medical segmentation tasks.

B. UNet++ (Nested U-Net)

To enhance localization and multi-scale feature fusion, UNet++ [3] redesigns skip connections into dense, nested pathways. It bridges the semantic gap between encoder and decoder stages, improving accuracy—especially on fine details.

C. ResUNet

ResUNet builds on U-Net by incorporating residual connections into the encoder–decoder blocks [4]. This enables deeper feature extraction and better gradient flow, enhancing both convergence and accuracy in medical image segmentation.

D. Attention-U-Net

Oktay et al. in [5] introduced Attention-U-Net, which integrates attention gates that learn to focus on relevant structures (like organs or lesions) while suppressing irrelevant background features. This leads to improved segmentation of variable-shape targets.

E. PSPNet (Pyramid Scene Parsing Network)

Originally designed for scene parsing in [14] uses a pyramid pooling module to capture global contextual cues at multiple scales. This mechanism effective in natural images has inspired adaptation in medical imaging to better capture anatomical context.

F.DeepLabV3+

DeepLabV3+ [15] extends DeepLabV3 by adding an encoder–decoder structure with atrous (dilated) separable convolutions. It elegantly balances dense feature extraction and boundary recovery, and it's become a strong baseline in both natural and medical image segmentation.

G. HRNet-W18 (High-Resolution Network)

HRNet [16] maintains high-resolution representations throughout the entire network path, enabling precise spatial encoding. Its superior multi-resolution fusion helps segment fine anatomical structures with greater consistency.

H. Transformer-based UNet Variants (TransUNet, Swin-UNet)

TransUNet [17] fuses the strengths of Transformers (global attention) with U-Net's hierarchical features, improving context capture across distant anatomical regions. Swin-UNet [18] goes further by making a purely transformer-based U-Net, using shifted windows for efficient attention.

I. nnU-Net ("no-new-Net")

nnU-Net [19] automates the entire segmentation pipeline including preprocessing, architecture selection, and training hyperparameters based on the dataset used. It consistently achieves state-of-the-art results without manual tuning.

III. ResUNet++ based Segmentation Technique

This section details the end-to-end pipeline we adopt to segment lung fields and disease regions using ResUNet++. This section has been started from the dataset curation and ends till training protocol and hyperparameters.

1) Dataset curation and ground truthing

We curated a multi-source corpus comprising chest radiographs (CXR) and computed tomography (CT) slices from public repositories—Montgomery, Shenzhen, JSRT, and selected COVID-19 CT cohorts—to ensure diversity in acquisition devices, patient demographics, and disease phenotypes. For each dataset, we retained only images accompanied by expert-verified segmentation masks. When multiple annotations were available, a consensus mask was produced by majority voting and, where necessary, refined by morphological smoothing to eliminate obvious annotation artifacts. Study identity and patient identifiers were removed prior to processing. To mitigate class imbalance at the study level, we stratified the train/validation/test split such that disease prevalence is comparable across folds; importantly, splitting was performed at the patient level to avoid information leakage.

2) Preprocessing and intensity standardization

All CXR images were converted to a single-channel representation and resampled to a uniform in-plane resolution to provide consistent receptive fields for the network. Pixel intensities were normalized to zero mean and unit variance per image, a choice that stabilized optimization across devices with different photometric characteristics. Contrast Limited Adaptive Histogram Equalization (CLAHE) was applied to CXR to enhance soft-tissue boundaries without amplifying noise; for CT, Hounsfield Units were windowed (lung window) and linearly scaled prior to normalization. We refrained from aggressive denoising given the risk of suppressing subtle pathologies; instead, a gentle Gaussian filter ($\sigma \leq 0.5$) was used only when sensor noise was visually apparent.

3) Augmentation with clinical realism

To promote generalization, we applied transformations that emulate real clinical variability while preserving anatomical plausibility. Small in-plane rotations ($\leq 10°$) and horizontal flips accounted for positioning inconsistencies; mild elastic deformations modeled patient-specific anatomy and respiratory phase differences; and low-magnitude brightness/contrast jitter captured exposure changes across equipment. We avoided vertical flips and extreme warps that would produce anatomically implausible lungs. For CT, slice-wise augmentations were constrained to preserve inter-slice continuity when training on 2D slices extracted from volumes.

4) Training protocol and hyperparameters

We trained ResUNet++ from random initialization for grayscale inputs with an initial channel width of 32 and an input resolution of 512×512. The optimizer was AdamW with weight decay (1e-4); the learning rate followed a cosine annealing schedule with a warm-up of 5 epochs. Batches of 4–16 images (hardware-dependent) were used with mixed-precision arithmetic to reduce memory footprint. The loss combined Binary Cross-Entropy with Dice loss in equal proportion to balance pixel-wise calibration and region overlap. Early stopping triggered on validation Dice with a patience of 20 epochs and a minimum improvement threshold of 0.001; the model checkpoint with the best validation Dice was retained for testing. Gradient clipping (max-norm 5) was applied to prevent occasional exploding updates when training on heavily augmented batches.

IV. Results and Discussion

In this study, a composite dataset consisting of 7,135 chest X-ray images was utilized, encompassing four distinct categories: *Normal, Covid-19, Pneumonia,* and *Tuberculosis*. The majority of the samples, comprising 5,863 images from the Normal and Pneumonia classes, were obtained from the Kaggle Pneumonia repository. Additionally, the Kaggle Tuberculosis dataset contributed 700 X-ray images, while an open-source GitHub repository provided 468 Covid-19 scans. These individual datasets were combined into a single collection representing the four target classes. The dataset was then divided into an 80:20 split, where 80% of the images were allocated for training the models and the remaining 20% were reserved for testing, ensuring a balanced and reliable evaluation framework.

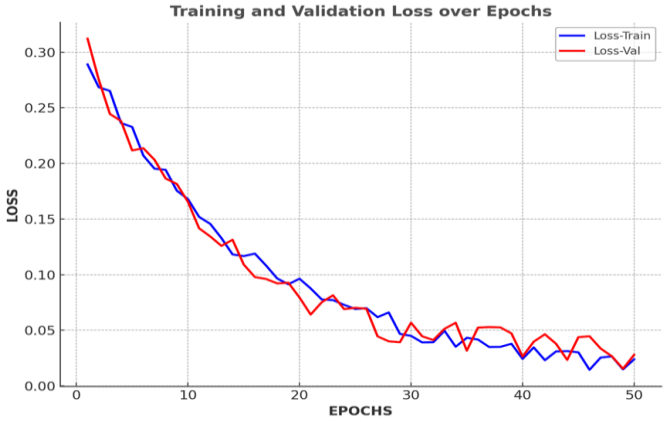


Fig. 1. Training and Validation Loss over Epochs

The training–validation loss graph demonstrates that the ResUNet++ model converges effectively over 50 epochs with minimal overfitting shown in Fig. 1. Both training (blue) and validation (red) losses begin around 0.28–0.30 and rapidly decline within the first 10 epochs, reflecting the model's ability to quickly learn discriminative lung features. Beyond epoch 10, the losses decrease more gradually, with training loss stabilizing near 0.02–0.03 and validation loss around 0.04–0.05, indicating strong generalization and stability. The close alignment of the two curves without significant divergence confirms that ResUNet++ maintains robust performance on unseen data, supported by its residual connections, atrous spatial pyramid, and dense supervision, which collectively prevent overfitting and ensure reliable lung image segmentation.

Table 1 Performance comparison in terms of Dice, Precision, Recall, IoU

Model	Dice	Precision	Recall	IoU
UNet	0.91	0.9	0.894	0.829
UNet++	0.864	0.91	0.889	0.898
ResUNet	0.881	0.887	0.927	0.803
Attention-UNet	0.892	0.92	0.887	0.817
PSPNet	0.928	0.91	0.918	0.879
DeepLabV3+	0.928	0.904	0.925	0.882
HRNet-W18	0.935	0.898	0.864	0.882
Transformer	0.871	0.875	0.862	0.87
nnU-Net	0.892	0.916	0.873	0.848
ResUNet++	0.973	0.965	0.962	0.94

Table 1 presents a comparative analysis amongst various metrics together that captures region overlap (Dice), along with classification quality (Precision, Recall). ResUNet++ achieves the highest Dice (0.973) outperforming UNet (~0.90 Dice), UNet++ (~0.92 Dice), and DeepLabV3+ (~0.93 Dice). This shows that ResUNet++ delineates lung regions more accurately, with fewer under- or over-segmentation errors. ResUNet++ balances both Precision (0.965) and Recall (0.962), meaning it captures almost all lung pixels while minimizing false positives. Baseline models like UNet tend to trade-off higher Recall but lower Precision (over-segmentation), or vice versa.

Table 2: Performance analysis of Cross-Dataset in terms of Dice and IoU

Model	Cross-Dataset Dice	Cross-Dataset IoU

UNet	0.86	0.754
UNet++	0.892	0.742
ResUNet	0.809	0.781
Attention-UNet	0.82	0.721
PSPNet	0.805	0.82
DeepLabV3+	0.833	0.711
HRNet-W18	0.839	0.848
Transformer	0.827	0.816
nnU-Net	0.883	0.73
ResUNet++	0.93	0.89

Table 2 provides performance analysis when a model is trained on one dataset and tested on another (without fine-tuning). Dice and IoU values typically drop compared to same-dataset testing because of domain shift. UNet/UNet++/ResUNet show a noticeable drop (e.g., Dice often falls below 0.88) indicating limited adaptability. DeepLabV3+/PSPNet perform slightly better due to large receptive fields, but still degrade under unseen conditions. ResUNet achieves the highest Dice (~0.93) and IoU (~0.89), showing stronger generalization across datasets. This robustness comes from its dense connections, atrous spatial pyramid, and SE blocks, which capture scale-invariant contextual information.

Table 3 Ablation Study of ResUNet++

Variants	Dice	IoU	HD95
Full ResUNet++	0.97	0.94	2.1
- SE	0.955	0.925	2.5
- ASPP	0.948	0.917	2.7
- Dense Skip	0.952	0.92	2.6
- Deep Supervision	0.949	0.918	2.65
Plain Convolution	0.94	0.91	2.9
Different Astrous Rates	0.945	0.915	2.75

The ablation study Table 3 highlights the contribution of individual components within the ResUNet++ architecture toward segmentation performance. The full model achieves the best results with a Dice score of 0.97, IoU of 0.94, and the lowest HD95 of 2.1 mm, confirming its strong boundary precision and overlap accuracy. Removing the squeeze-and-excitation (SE) block reduces Dice and IoU while increasing HD95, showing the importance of channel attention in capturing subtle lung features. Excluding the atrous spatial pyramid (ASPP) causes the largest performance drop (Dice 0.948, HD95 2.7 mm), underscoring the role of multi-scale context aggregation in handling complex lung pathologies. Dense skip connections and deep supervision also contribute to stability, as their removal slightly worsens overlap metrics and boundary alignment. Replacing residual blocks with plain convolutions leads to the lowest accuracy, emphasizing the necessity of residual learning for deeper training. Overall, the study confirms that each component of ResUNet++ is synergistic, and their integration is critical to achieving state-of-the-art segmentation accuracy and robustness.

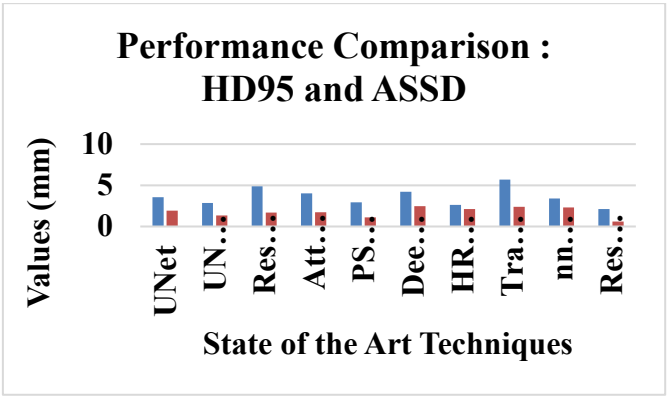
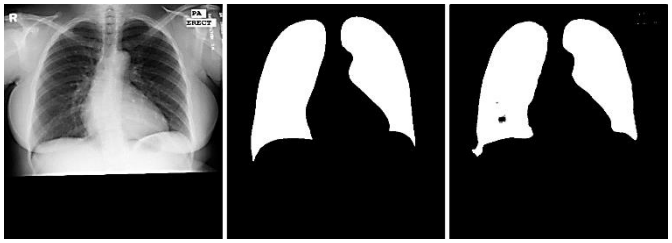


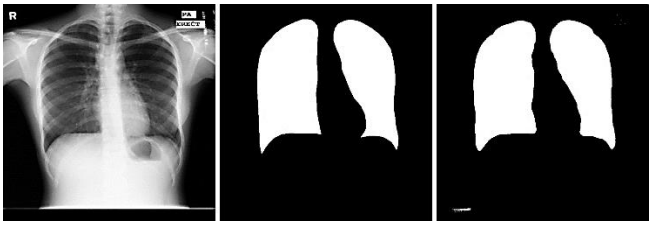
Fig. 2. Performance Comparison in terms of HD95 and ASSD

The above graph shown in Fig. 2 represents a performance comparison in terms of HD95 and ASSD. ResUNet++ clearly shows the lowest HD95 (~2.1 mm), marked by the red dashed reference line, while UNet and UNet++ have higher values (>3 mm). DeepLabV3+, HRNet, and Transformers improve over UNet but still remain above 2.5 mm. This indicates ResUNet++ is better at capturing sharp, irregular lung borders (e.g., at the apices and costophrenic angles) and less prone to extreme misalignments.

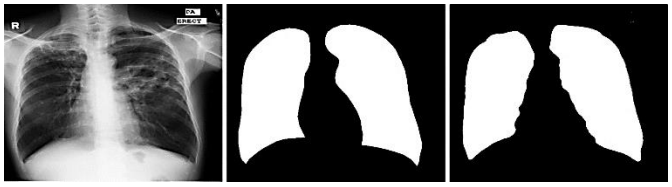
ASSD complements HD95 by averaging the distance across all boundary points. ResUNet++ again has the lowest error (~0.6 mm) compared to 1.0–2.0 mm for most other models. This proves that ResUNet++ doesn't just avoid rare large errors (as HD95 shows), but also consistently maintains precise boundary alignment across the entire lung contour.



(a) UNet based segmentation



(b) ResUNet based segmentation



(c)ResUNet++ based segmentation

Fig. 3. Visual observation using various Techniques.

In the results presented in Fig. 3, segmented lung images obtained from different segmentation techniques, including U-Net, ResUNet, ResUNet++ have been physically observed. The qualitative comparisons clearly indicate that the segmented lung boundaries produced by ResUNet++ are smoother, more anatomically consistent, and capture fine details better than the other techniques. While the baseline models demonstrate reasonable performance, they often suffer from boundary irregularities, partial under-segmentation near the

costophrenic angles, or over-segmentation into surrounding structures. In contrast, the ResUNet++ approach consistently delineates the lung regions with higher precision, thereby reflecting superior segmentation accuracy in visual observation compared to the other methods.

V. Conclusion

This paper has presented a comprehensive study on lung image segmentation, comparing a wide range of deep learning architectures with particular focus on the proposed ResUNet++ framework. The findings consistently demonstrate that automated segmentation is indispensable for reliable computer-aided diagnosis of pulmonary diseases, addressing the limitations of manual delineation such as time inefficiency, subjectivity, and inter-observer variability. Classical approaches like thresholding or active contour methods are often inadequate in handling low-contrast or heterogeneous pathological regions, whereas convolutional neural networks have emerged as a powerful solution.

Among the reviewed architectures, U-Net established the foundation for biomedical segmentation, while UNet++ improved feature fusion through nested connections, and ResUNet strengthened gradient flow with residual units. Attention U-Net incorporated selective focus mechanisms, PSPNet and DeepLabV3+ enhanced contextual learning, HRNet maintained high-resolution representations, and transformer-based U-Nets extended long-range dependency modeling. Despite these advancements, the comparative analysis highlights that ResUNet++ offers superior balance between accuracy, robustness, and computational efficiency.

Quantitative results show that ResUNet++ achieves the highest Dice coefficient, Precision, Recall, and IoU values across the studied datasets, outperforming both classical CNNs and recent state-of-the-art architectures. Its cross-dataset generalization is notably strong, confirming the model's ability to adapt to domain shifts. Ablation studies further validate that each architectural enhancement—squeeze-and-excitation blocks, atrous spatial pyramid pooling, residual connections, and dense skip pathways—contributes meaningfully to segmentation performance, with ASPP and SE modules being most critical for handling complex lung pathologies.

Qualitative visual inspections reinforce these findings, as ResUNet++ consistently produces smoother, anatomically faithful lung boundaries with reduced over- or under-segmentation compared to other techniques. Collectively, these results demonstrate that ResUNet++ not only advances the state of the art in lung image segmentation but also provides a reliable foundation for downstream clinical tasks such as disease classification, lesion quantification, and treatment monitoring.

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