MAIA

Prior-Aware Autoencoders for Lung Pathology Segmentation

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Problem Statement

"Varied lung pathologies with diverse characteristics such as size, shape, location, and texture pose a significant obstacle for accurate and reliable segmentation due to their similarity to surrounding tissues, demanding advanced methods for precise identification"

CT Datasets for Segmentation

- **LIDC-IDRI dataset**
  - 2625 nodules with more than 15,000 pathological slices

- **Non-Small Cell Lung Cancer (NSCLC) datasets**
  - **Source 1:** NSCLC-Radiomics dataset
  - 421 patients with 7355 pathological slices
  - **Source 2:** Medical Segmentation Decathlon dataset
  - 1657 pathological slices

- **Covid-19 Infection datasets**
  - **Source 1:** Corona cases dataset
  - 1351 pathological image slices
  - **Source 2:** Covid19 Challenge (synthetic CT volumes)
  - 10,031 pathological images

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Proposed Framework

- The proposed framework consists of three different modules

1. **Partial Convolutional Neural Network (PCNN)**
2. **Normal Appearance Autoencoders (NAA)**
3. **Prior U-Net**

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Partial Convolutional Neural Network

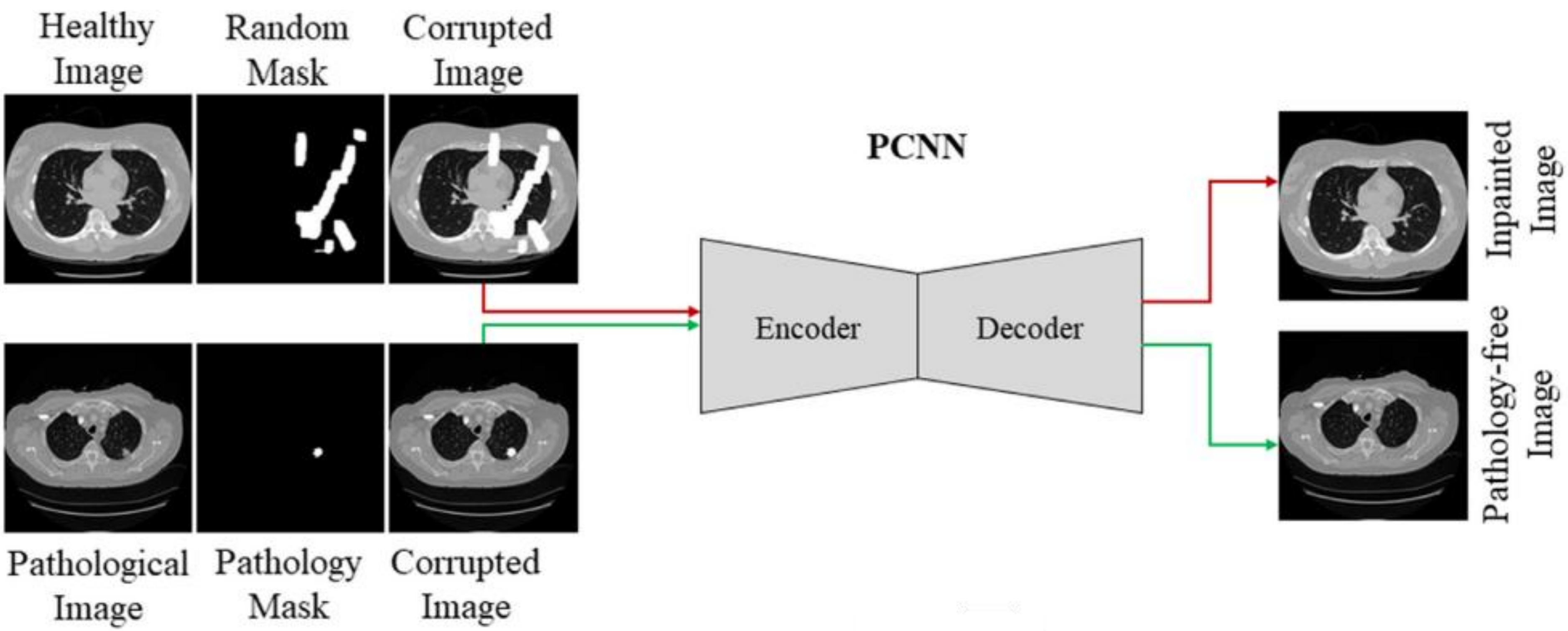

Figure 1. Partial Convolutional Neural Network Architecture

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Partial Convolutional Neural Network

- **Inpainting Model**

- Create synthetic pathology-free images from pathological lung images.

- **Partial Convolutional Operator**

- Smooth filling of irregularly shaped pathological regions using nearby healthy tissue patterns.

- **Segmentation Labels as Input**

- for the generation process of synthetic pathology-free images.

Normal Appearance Autoencoder

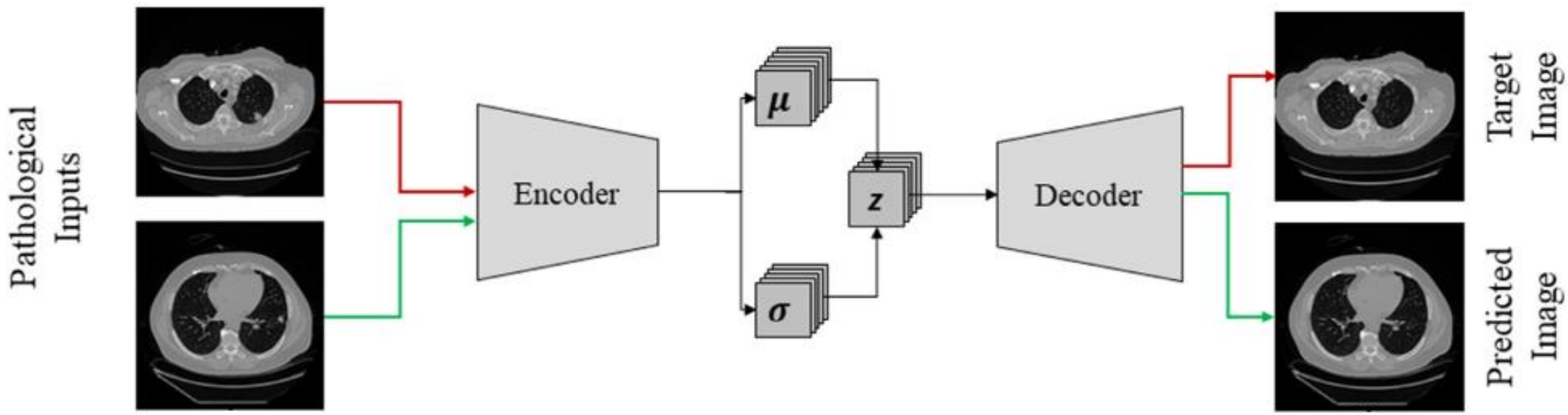


Figure 2. Normal Appearance Autoencoder

Normal Appearance Autoencoder

The normal appearance autoencoder (NAA) is a modified variational autoencoder.

Key modifications include:

- Supervised Training
- Convolutional Layers
- Regularization Term
- Reconstruction Loss Weighting

Normal Appearance Autoencoder

To assess the effectiveness of the NAA model in automatically reconstructing pathology-free images, a postprocessing framework was implemented and this involves:

- Residual Calculation
- Aggregation and Masking
- Otsu Thresholding
- Morphological Operations

Prior U-Net

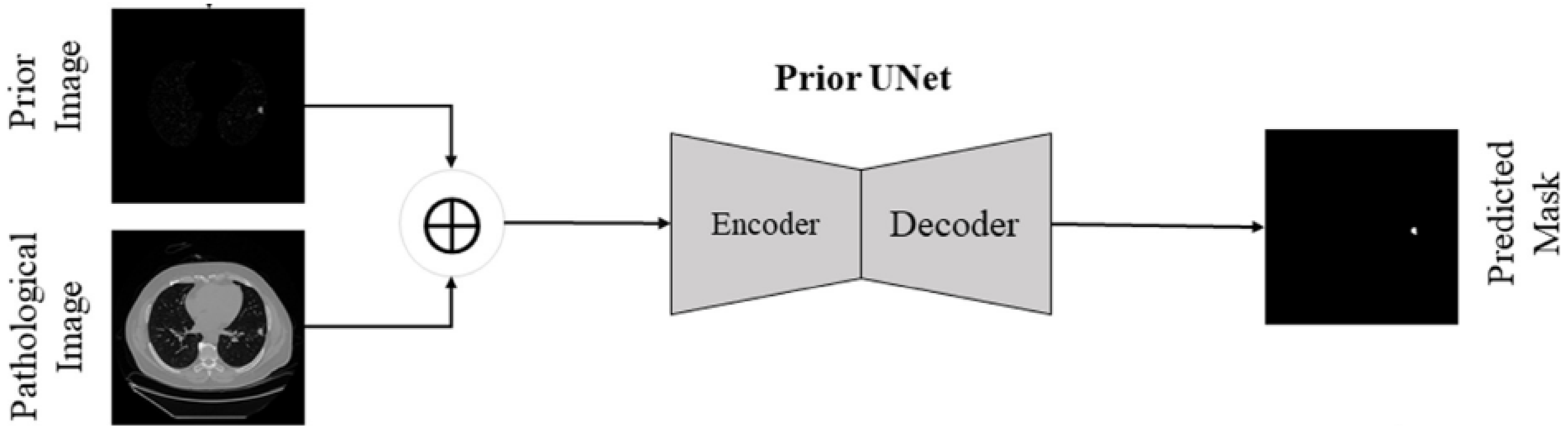


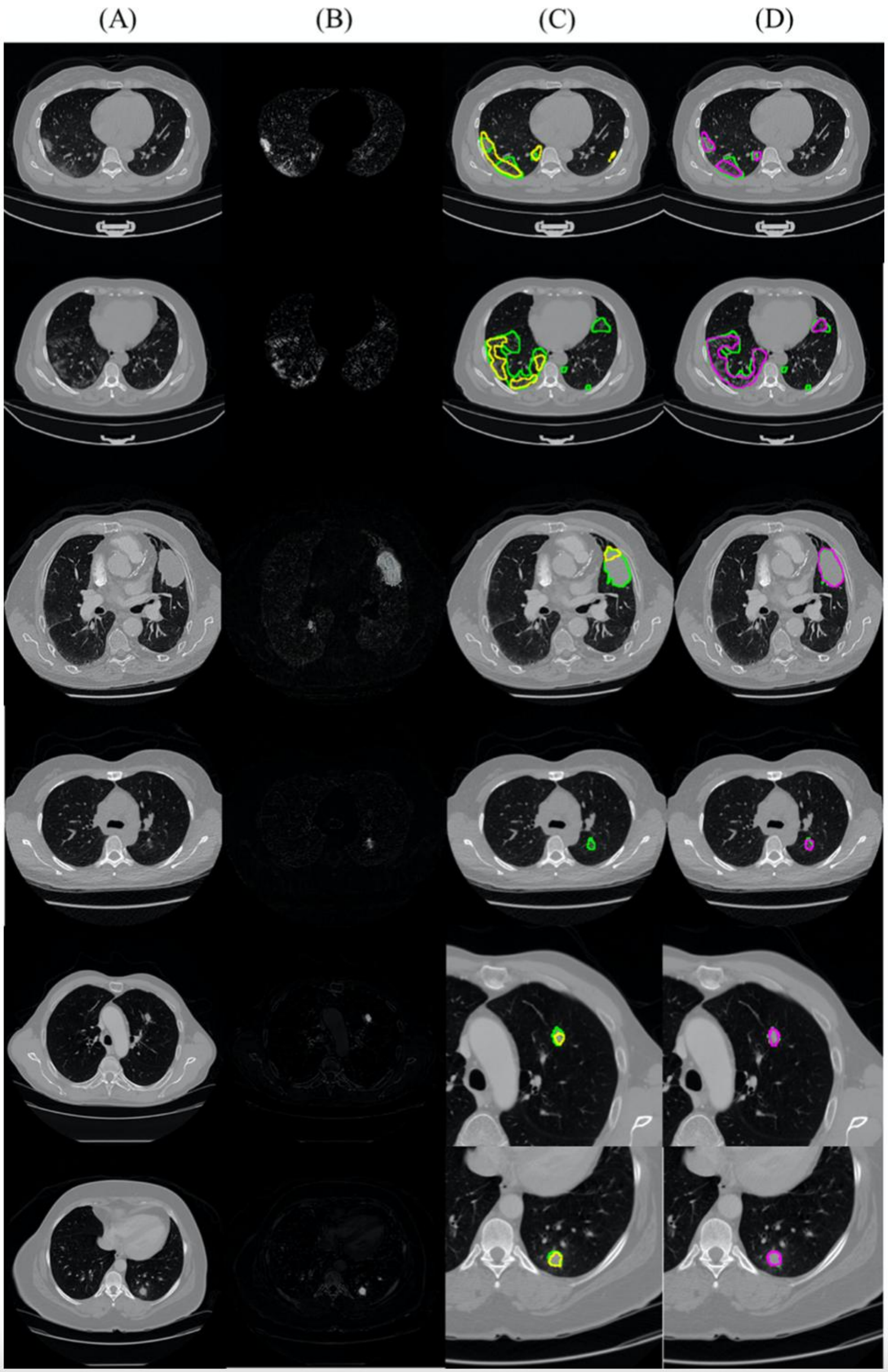
Figure 3. Prior U-Net

Prior U-Net

- Differences between the pathological image and reconstructed lesion-free image predicted by the NAA model were considered as prior knowledge and combined with the main image to train a two-channel prior U-Net.

Evaluation Criteria

- The proposed pipeline was tested on three types of lung pathologies, including pulmonary nodules, Non-Small Cell Lung Cancer (NSCLC), and COVID-19 lesions on five comprehensive datasets.
- To evaluate the performance of the proposed segmentation model. We employ several metrics, including
  - Dice coefficient
  - Precision
  - Recall
  - Average Surface Distance (ASD)
  - Hausdorff Distance (HD) to quantify the comparisons.



Results

- Examples of segmented lung pathologies including **Covid19-lesions** (the first two rows), **NSCLCs** (the second two rows), and **lung nodules** (the last two rows).
- **Column A**: pathological images.
- **Column B**: Prior images calculated from the prediction of the NAA model.
- **Column C**: Segmentation agreement between the baseline model (yellow) and target masks (green).
- **Column D**: Segmentation agreement between the prior model (cyan) and target masks (green).

Results

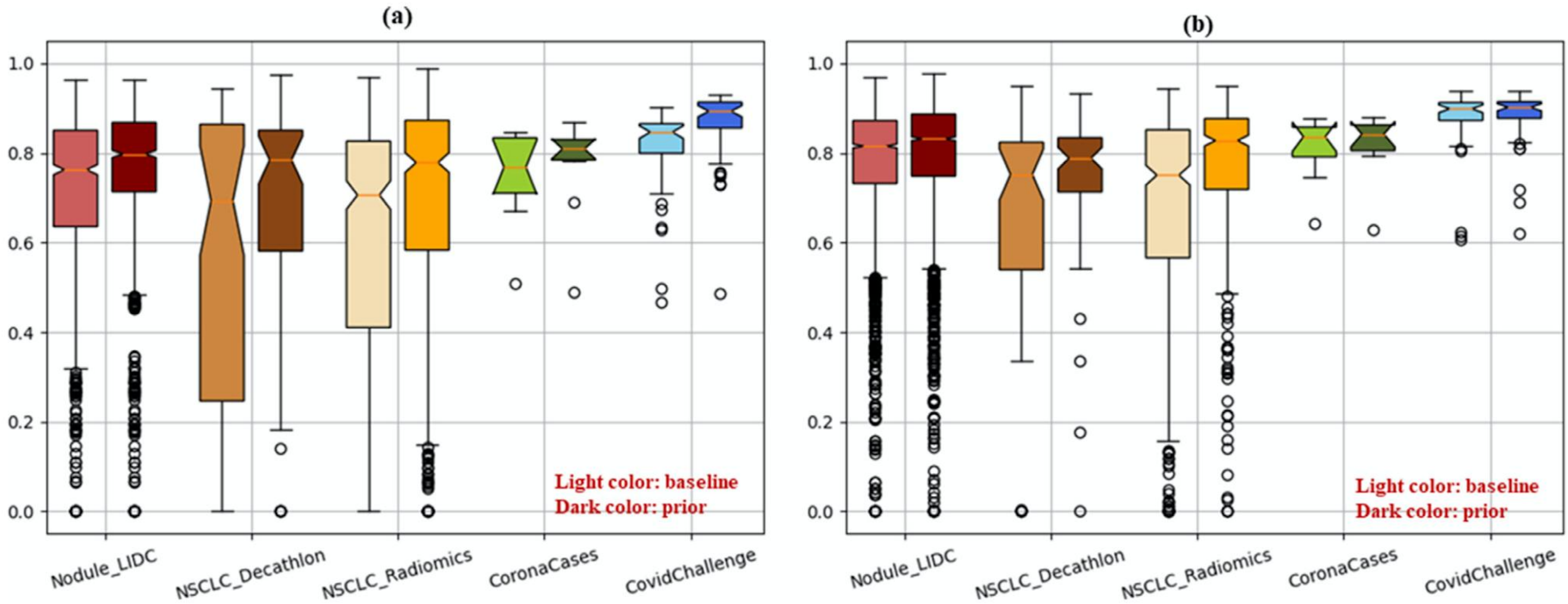


Fig. 6. Comparison of the Dice scores between the baseline models and prior models in (a) our implementation and (b) nn-U-Net model. The results show that prior models outperform the baseline method for all the datasets both in our implementation and standard nn-U-Net.

Results

Results of lung pathology segmentation reported in other publications using the same datasets against the best performance achieved by the proposed method.

Pathology-Data	Model Name	Description	Reported Dice	Our Dice
Nodule-LIDC	CF-CNN(Wang et al., 2017)	subset of 893 nodules, 35×35×35 patches	0.821	0.795±0.138
	CoLe-CNN (Pezzano et al., 2021)	subset of 493 nodules, 64×64 patches	0.861	
	CDP-ResNet (Liu et al., 2019)	subset of 986 nodules, 35×35×3 patches	0.815	
	UNet++ (Zhou et al., 2020)	1012 cases, 64×64×64 patches	0.772	
NSCLC-Decathlon	nn-UNet (Isensee et al., 2018)	3D cascade UNet	0.668	0.741±0.167
NSCLC-Radiomics	Dilated CNN (Mohammadi et al., 2019)	2D slices	0.594	0.767±0.173
Covid19-Coronacases	nn-UNet (Yao et al., 2020)	2D slices	0.801	0.819±0.068

The addition of the prior model improved the Dice coefficient for:-

- Lung nodule segmentation by **0.038**,
- NSCLC segmentation by **0.101**, and
- Covid-19 lesion segmentation by **0.041** on average.

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Conclusion and Future Scope

The prior knowledge obtained from the NAA model, which represents the shape and location of lung pathologies, is integrated into a segmentation network to guide more accurate delineations.

The results demonstrate that the NAA model produces reliable prior knowledge about lung pathologies, and integrating this knowledge into a segmentation network leads to more accurate segmentation results.

Future work includes combining the NAA model with an inpainting model to automatically synthesize pathology-free images and integrating the obtained prior information into a cascading segmentation network with a layer-wise attention mechanism.

References

[1] Mehdi Astarakia, b, Örjan Smedbya, Chunliang Wanga., “Prior-aware autoencoders for lung pathology segmentation”. Elsevier B.V. p. https://doi.org/10.1016/j.media.2022.102491, 2022.

[2] Liu, G., Reda, F. A., Shih, K. J., Wang, T., Tao, A., & Catanzaro, B. (2018). Image Inpainting for Irregular Holes Using Partial Convolutions. ArXiv. /abs/1804.07723

Thank you for your attention! ☺