

NIT AP CSE

EPICS MINI PROJECT EP258

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RIBS IDENTIFICATION AND DISEASE DETERMINATION

~Using Deep Learning Segmentation techniques



RIBS IDENTIFICATION

- Using Deep Learning to study the Structure and Positioning of Anterior and Posterior Ribs
- Chest radiography (chest X-ray or CXR) is an economical and easy-to-use medical imaging and diagnostic technique. The technique is the most commonly used diagnostic tool in medical practice and has an important role in the diagnosis of the lung disease
- Deep learning (DL) has shown superior performance to other methods in the segmentation and labeling of individual ribs

- A wide range of diagnostic tasks can benefit from an automatic system that is able to segment and label individual ribs on chest X-ray (CXR) images. To this end, traditional approaches exploited hand-crafted features to identify the ribs, but failed with anterior ribs. Recently, deep learning (DL) has shown superior performance to other methods in the segmentation and labeling of individual ribs
- VinDr-RibCXR a benchmark dataset for the automatic segmentation and labeling of individual ribs on CXRs has been used for reference



DISEASE DETERMINATION

- chest radiographs are widely used in the detection and diagnosis of the lung diseases, such as pulmonary nodules, tuberculosis, and interstitial lung disease. Chest radiography contains a large amount of information about a patient's health

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- Developing DL algorithms for this task requires annotated images for each rib structure at pixel-level. To the best of our knowledge, there exists no such benchmark datasets and protocols. Hence, we introduce a new benchmark dataset, namely VinDr-RibCXR, for automatic segmentation and labeling of individual ribs from chest X-ray (CXR) scans
 - DICOM stands for Digital Imaging and Communications in Medicine. It is **a standard, internationally accepted format to view, store, retrieve and share medical images**. DICOM conforms to set protocols to maintain accuracy of information relayed through medical images

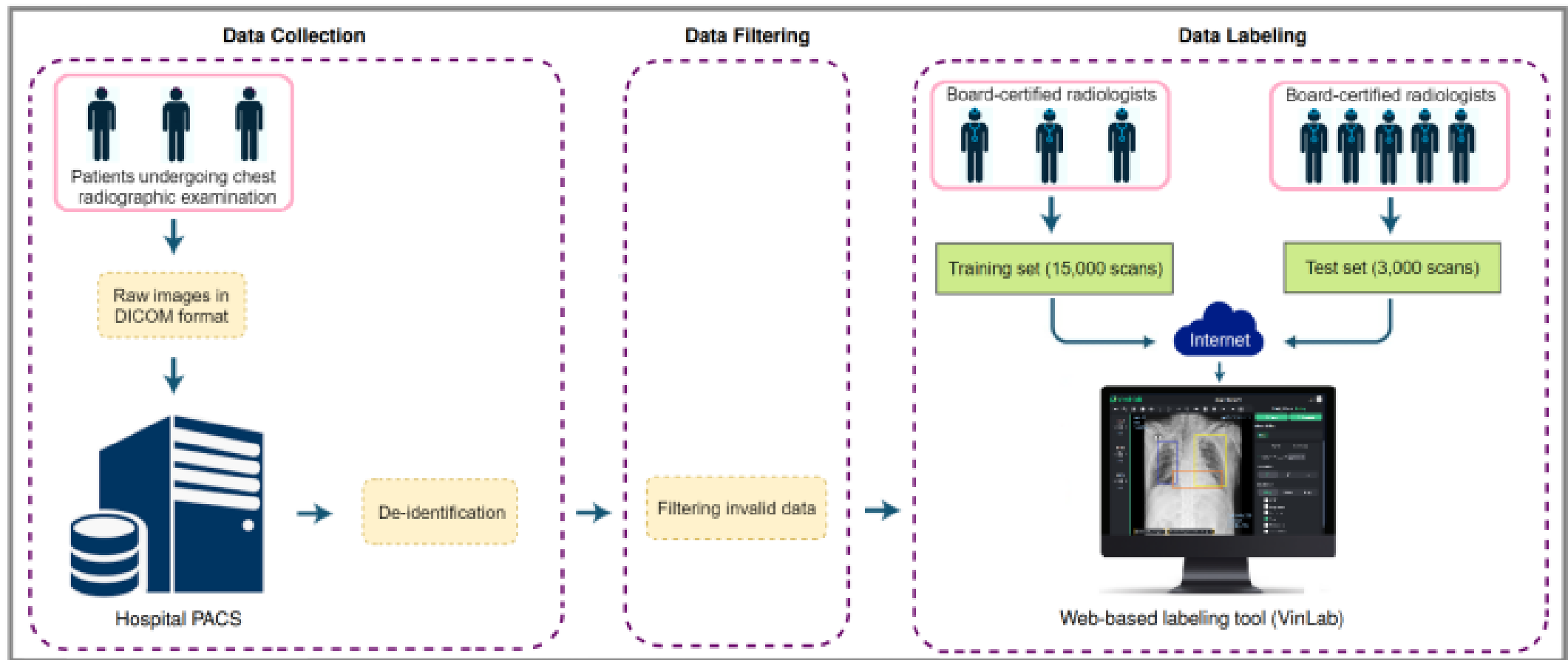


The building of VinDr-CXR dataset is divided into three main steps:

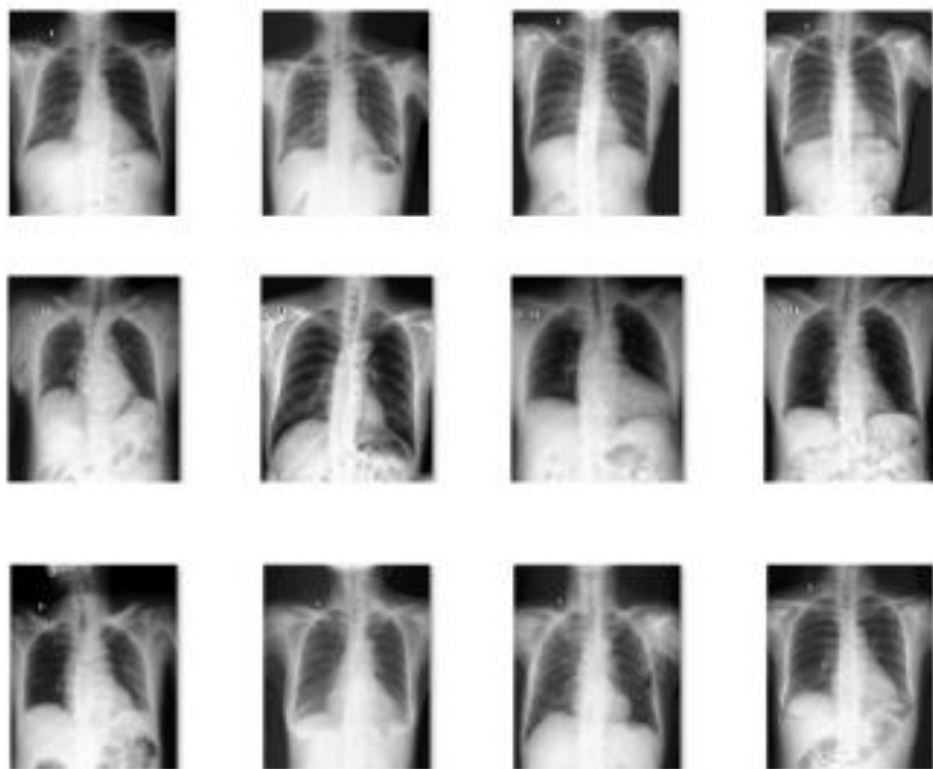
A Data collection

B Data filtering

C Data labeling



THE BUILDING OF VinDr-CXR DATASET



Valid images



Outlier images

PUBLIC DATASETS FOR CXR INTERPRETATION

Dataset	Release year	# findings	# samples	Image-level labels	Local labels
JSRT ¹⁴	2000	1	247 ^(c,*)	Available	Available
MC ¹⁶	2014	1	138 ^(c,*)	Available	N/A
SH ¹⁶	2014	1	662 ^(c,*)	Available	N/A
Indiana ¹⁵	2016	10	8,121 ^(c,*)	Available	N/A
ChestX-ray8 ¹⁰	2017	8	108,948 ^(*)	Available	Available ^(†)
ChestX-ray14 ¹⁰	2017	14	112,120 ^(*)	Available	N/A
CheXpert ³	2019	14	224,316 ^(*)	Available	N/A
Padchest ¹¹	2019	193	160,868 ^(*,*)	Available	N/A ^(††)
MIMIC-CXR ¹²	2019	14	377,110 ^(*)	Available	N/A
VinDr-CXR (ours)	2020	28	18,000 ^(*)	Available	Available

- Moderate-size datasets that are not applicable for training deep learning models

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- Dataset namely VinDr-RibCXR, of 245 AP/PA CXR images for segmentation and labeling of individual ribs
 - To develop and evaluate segmentation algorithms, the whole dataset into a training set of 196 images and a validation set of 49 images.

Various state-of-the-art DL-based segmentation models can be used for the task of individual rib segmentation and labeling

These models are well-known to be effective for many medical image segmentation tasks



Vanila U-Net

U-Net with
EfficientNet-B0

Feature Pyramid
Network (FPN)

U-Net++

Data set contains raw images in DICOM format

in-house web-based labeling tool called VinDr Lab that allows to segment individual ribs at pixel-level on DICOM scans

After Masking the Images are stored in JSON file

CONVOLUTIONAL NEURAL NETWORK(CNN)

- A Convolutional Neural Network (CNN or ConvNet) is a class of deep neural networks, that are typically used to recognize patterns present in images
- VanilaUnet ,FPN,U-net++,Unet with efficient netB0 are Fully Convolution neural network for image sematic segmentation

MODEL

```
Import segmentation_models_pytorch as smp
```

```
Model = smp.Unet(
```

```
    encoder_name="resnet50",
```

```
    encoder_weight="imagenet",
```

```
    channel_multiplier=1,
```

```
    pooling="adaptive pooling"
```

```
    in_channels=cfg.DATA.INP_CHANNEL
```

```
)
```

POSTERIOR - ANTERIOR (PA)

To obtain the front view

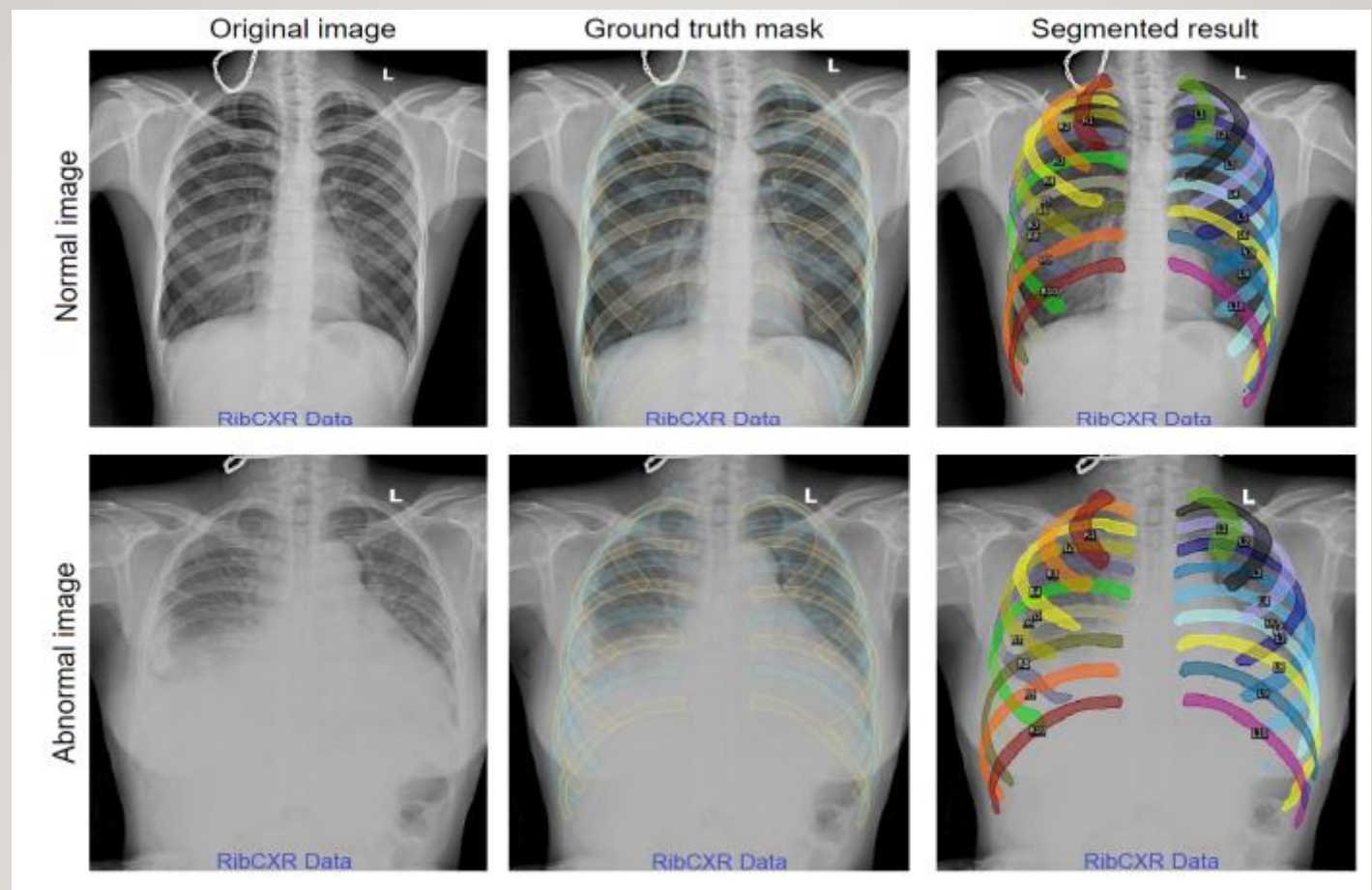
Posterior - Anterior (PA). This is the most common and preferred type of chest X-Ray. Posterior - anterior refers to the direction of the X-Ray beam travel; i.e. X-Ray beams hit the posterior part of the chest before the anterior part.



ANTERIOR - POSTERIOR (AP)

This type of chest X-Ray is generally less preferred because the image of the heart and mediastinum is less clear and focused in this projection







Image



1/1



Series

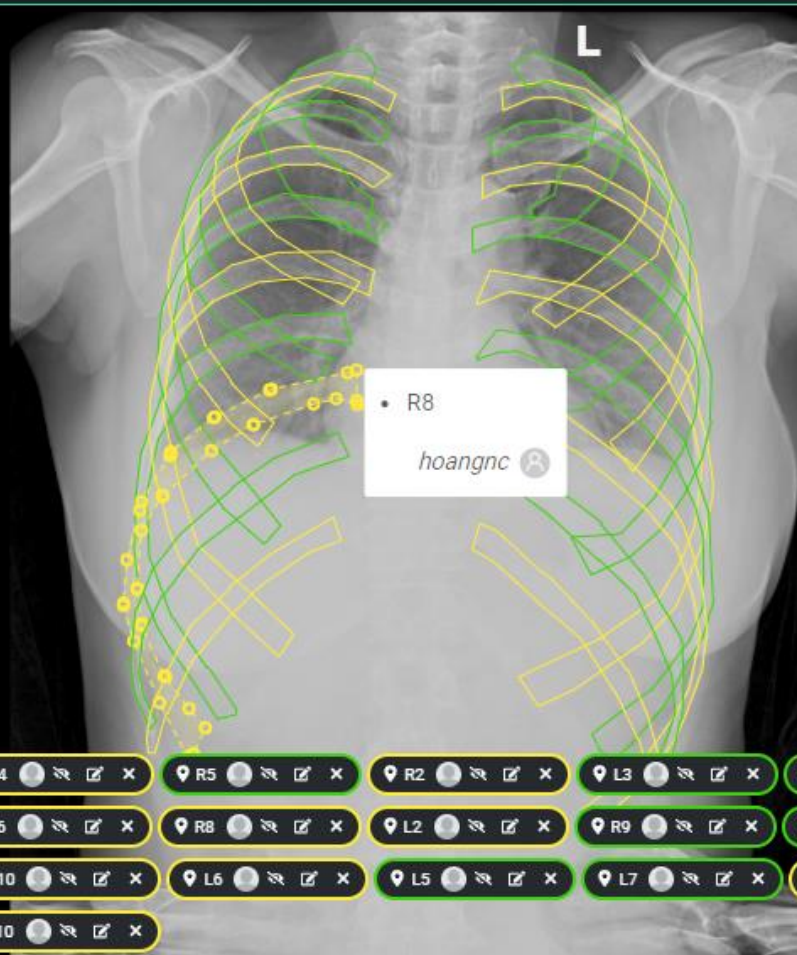


1/1

Study



1/1



Age: 000Y
Patient Sex: Male

Size: 2540 x 3072
Zoom: 19%
W: 65535 L: 34767

Task status: **Completed**

Save

Complete

Select labelers

hoangnc

Tools

Summary

Study Findings:

R3

1

R4

1

R5

1

R2

1

R1

1

Hide annotations



Hide active box





Image

< 1/1 >

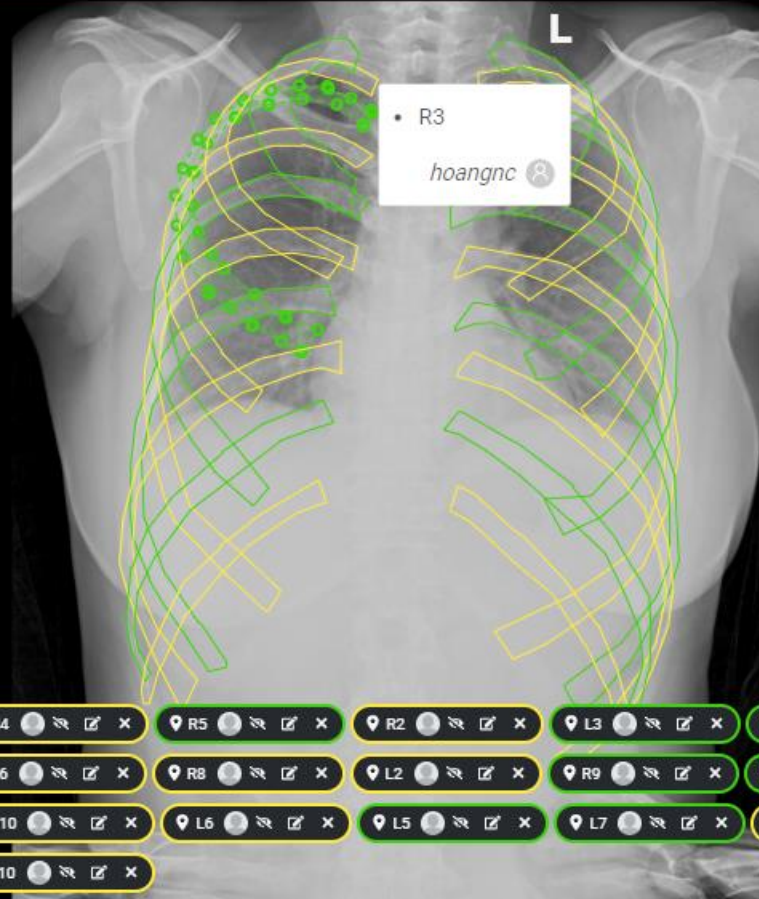


Series

< 1/1 >

Study

< 1/1 >



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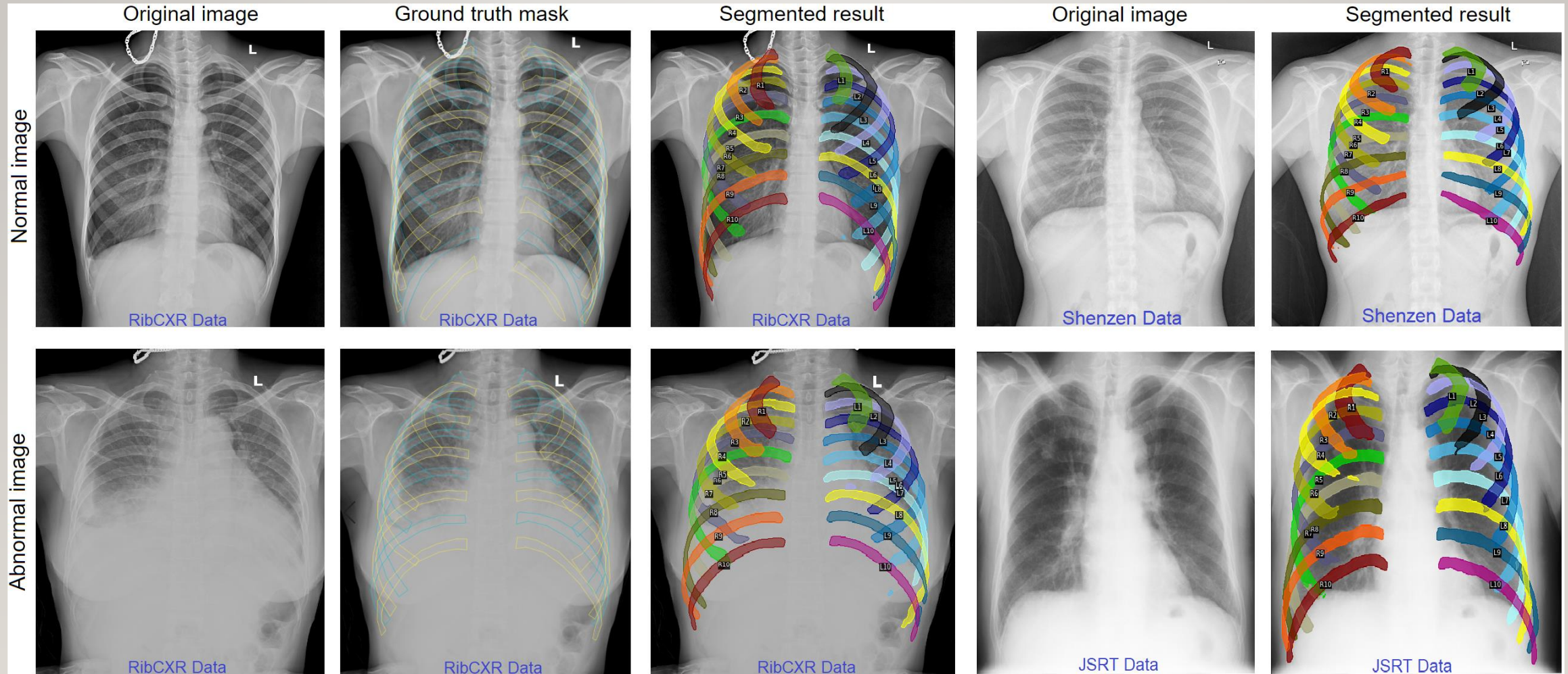
R1

1

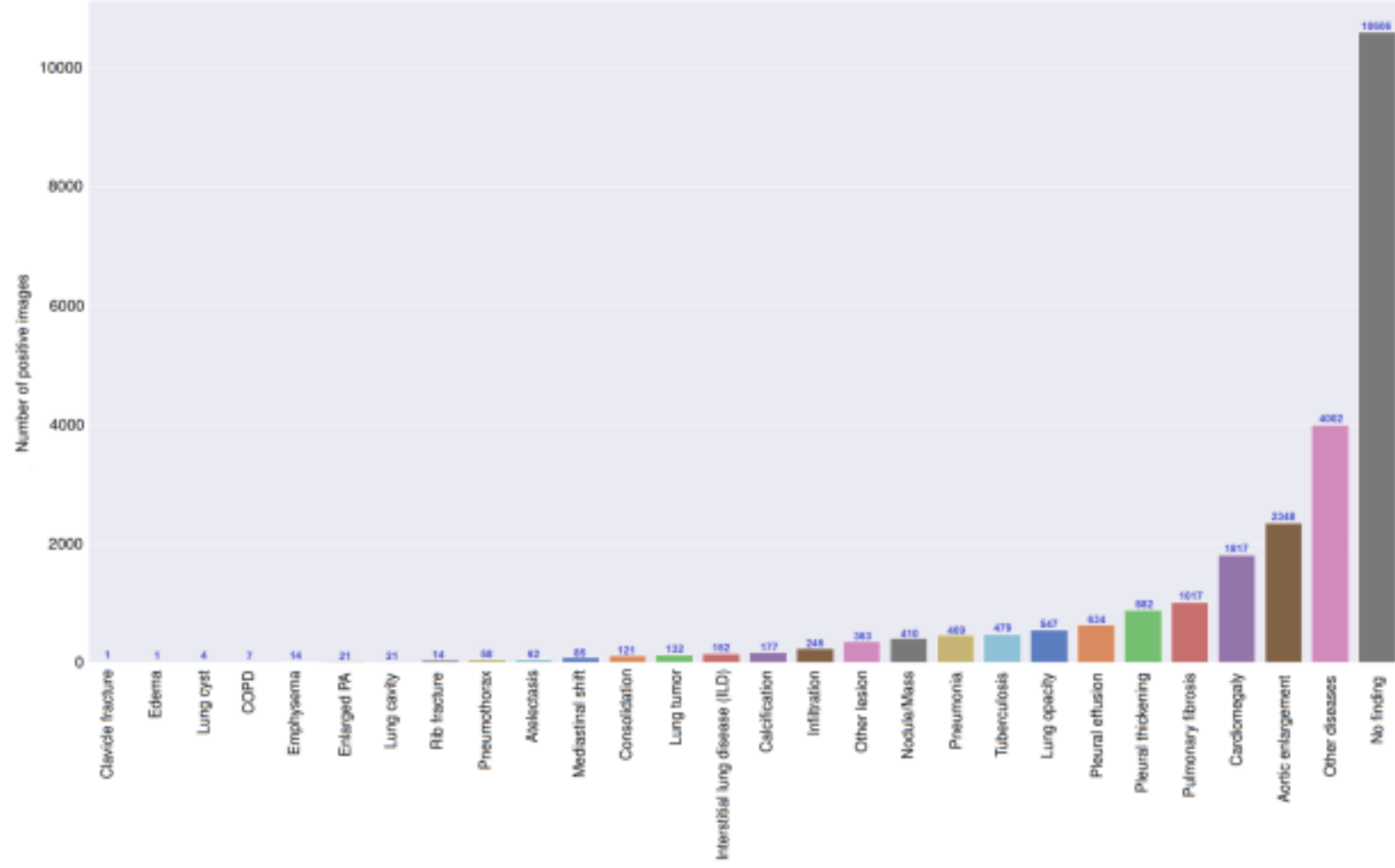
Hide annotations

Hide active box

Validating Segmentation results using various DataSets :-



The Figure shows segmentation and labeling results of the Nested U-Net on some representative cases from the validation set of VinDr-RibCXR and external datasets including JSRT and Shenzen.



PERFORMANCE RESULTS:-

Table 1: Segmentation performance on the validation set of VinDr-RibCXR.

Model	Dice	95% HD	Sensitivity	Specificity
U-Net	.765 (.737-.788)	28.038 (22.449-34.604)	.773 (.738-.791)	.996 (.996-.997)
U-Net w. EfficientNet-B0	.829 (.808-.847)	16.807 (14.372-19.539)	.844 (.818-.858)	.998 (.997-.998)
FPN w. EfficientNet-B0	.807 (.773-.824)	15.049 (13.190-16.953)	.808 (.773-.828)	.997 (.997-.998)
U-Net++ w. EfficientNet-B0	.834 (.810-.853)	15.453 (13.340-17.450)	.841 (.812-.858)	.998 (.997-.998)

The effectiveness of the segmentation models was evaluated by Dice score, 95% Hausdor distance (95% HD), sensitivity, and specificity.



Thankyou