Deep Learning Methods for Automatic Evaluation of Lines In Chest Radiographs

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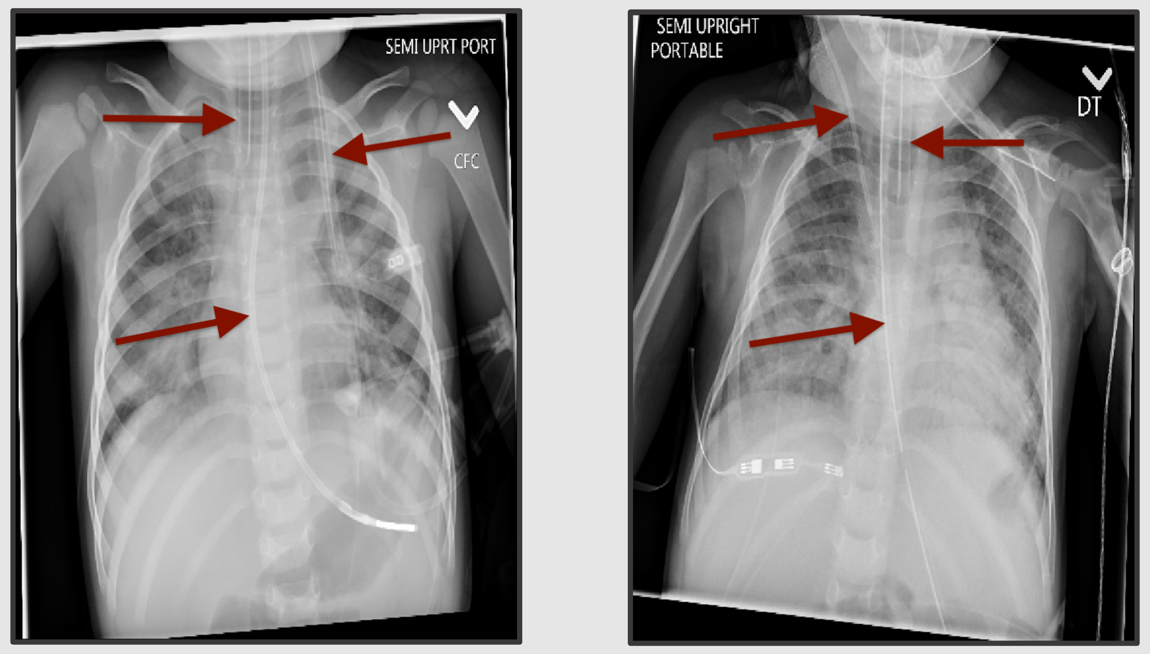
INTRODUCTION

- Catheters, lines, and tubes, collectively called **lines**, are used in a variety of medical procedures.



- **Misplaced** lines can cause dangerous **complications**.
- Radiologists examine **chest radiographs** (X-rays) to evaluate the placement of these lines.
- Before we can evaluate lines automatically, we must first **segment** them from the image background.
- We **semantically segment** lines in pediatric chest radiographs using **U-Net style, deep convolutional neural networks**.

METHOD

- Annotated 96 chest radiographs containing lines to create binary segmentation masks.
- Replaced the U-Net model encoder path with a variety of **backbones –** deep CNN feature encoders.
- We trained the network using **dice loss** to solve the class imbalance. (~97% of pixels are background)
  - **Generalized Dice loss** measures the overlap between the predicted mask and the true mask.

$$1 - 2\sum_{n}\sum_{c}\frac{(y_{n,c} * p_{n,c})}{(y_{n,c} + p_{n,c})}$$

- n = pixel
- c = class
- $y_{n,c}$ = 1 if n belongs to c, 0 otherwise
- $p_{n,c}$ = the probability predicted by the model that n belongs to class c

Our deep learning model automatically highlights **catheters**, **lines**, and **tubes** in chest X-rays.

RESULTS

a) ResNet50 b) ResNeXt101 c) EfficientNet B3

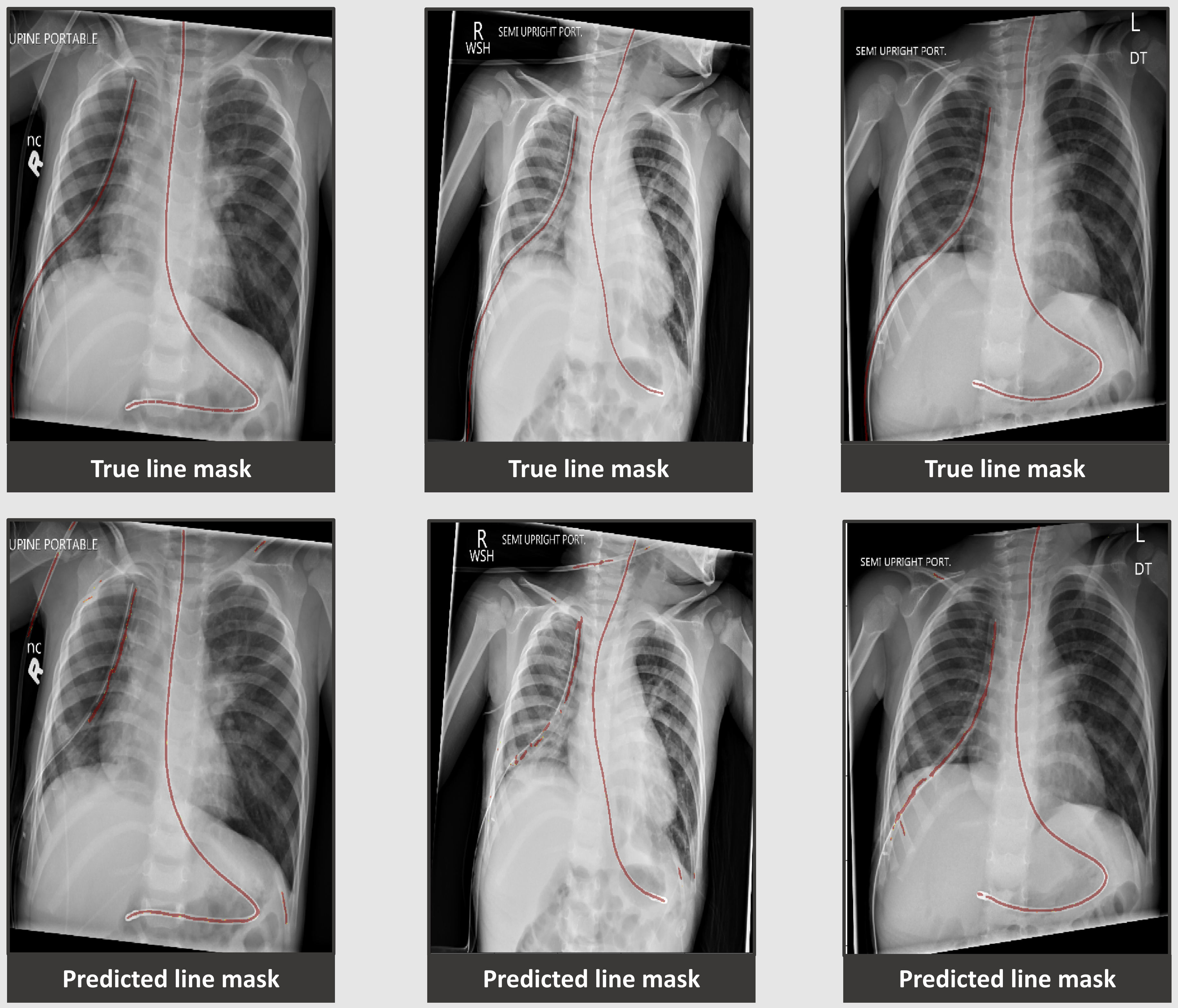


Figure 1: These results were obtained by training U-Net models with different encoder backbones on 512 x 512 images. The networks were initialized with ImageNet weights, and achieved a **dice scores** of **a) 0.527**, **b) 0.524**, and **c) 0.551** respectively on the test dataset. (Using a 70/15/15 train/validation/test split with n = 96)

CONCLUSIONS

- The EfficientNet-B3 backbone outperformed both ResNeXt101 and ResNet50.
- Training on dice loss resulted in better predictions than weighted binary cross entropy loss.
- Tests using a U-Net model with Feature Pyramid Networks (FPN) on the decoding path performed worse than models with the original U-Net decoder.

Model	Dice Coefficient	IoU (F score)
UNet-ResNet50	0.527	0.699
UNet-ResNeXt101	0.524	0.696
UNet-EfficientNetB3	**0.551**	**0.706**
FPN-ResNet50	0.498	0.676
FPN-ResNeXt101	0.492	0.675
FPN-EfficientNetB3	0.508	0.684

DISCUSSION

- Results could probably be improved by segmenting lines into **individual classes** for each type of line.
- A **larger dataset** of 200 samples should significantly improve results.
- **Data augmentation** methods could be applied to increase the value of the existing dataset.
- Using this segmentationmodel, new methods can be developed to automatically evaluate line placement in chest radiographs.

REFERENCES

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