Chest Radiograph Disentanglement for COVID-19 Outcome Prediction

Graph Deep Learning for Medical Applications

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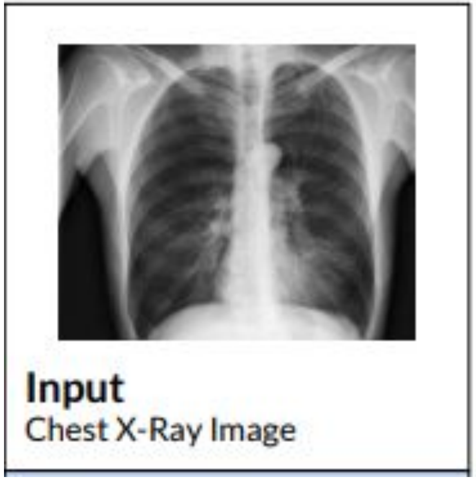
Introduction

Motivation

- Chest radiographs (CXRs) are the primary diagnostic tool for COVID-19 pneumonia
- Lung tissue texture may change drastically during hospitalization

AutoEncoder

- Swapping AutoEncoder successful disentanglement model
- LSAE learns a factorized representation of a CXR
- Terms texture and structure

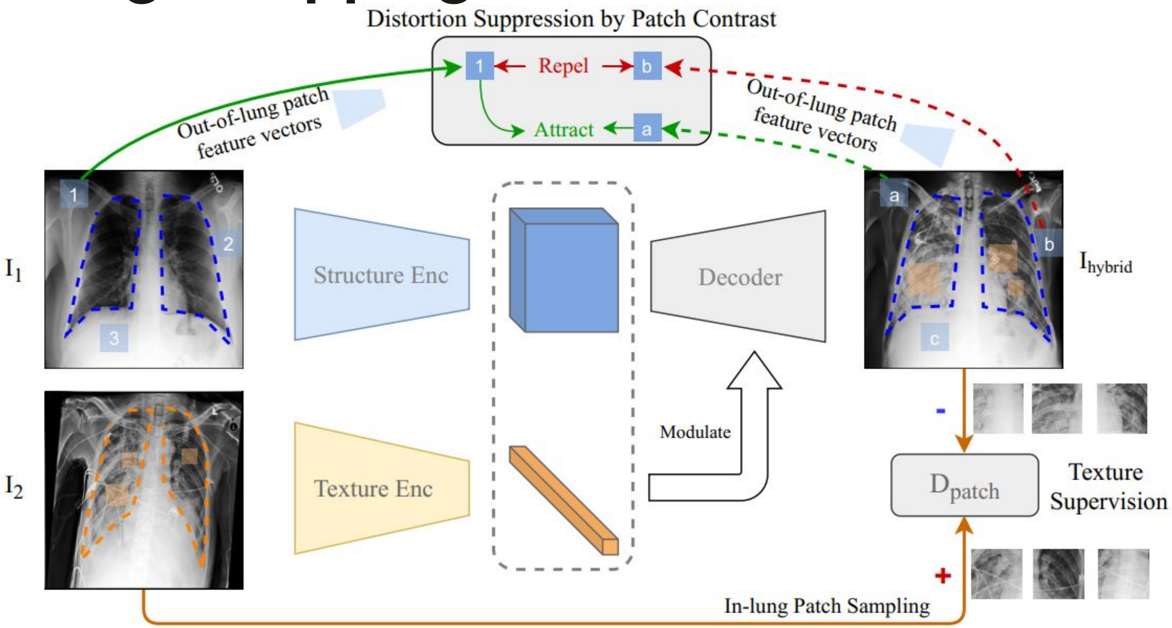


Methodology

Lung Swapping AutoEncoder (LSAE)

- ❖ vanilla SAE:
  - irrelevant textures diminish the effect of the texture transfer
  - irrelevant structure clues may leak into the hybrid image
- ❖ LSAE:
  - ➢ hypothesize that the out-of-lung irrelevant texture patterns may hinder target texture synthesis in Ihybrid .
  - ➢ two new features, in-lung texture supervision and out-of-lung structural distortion suppression

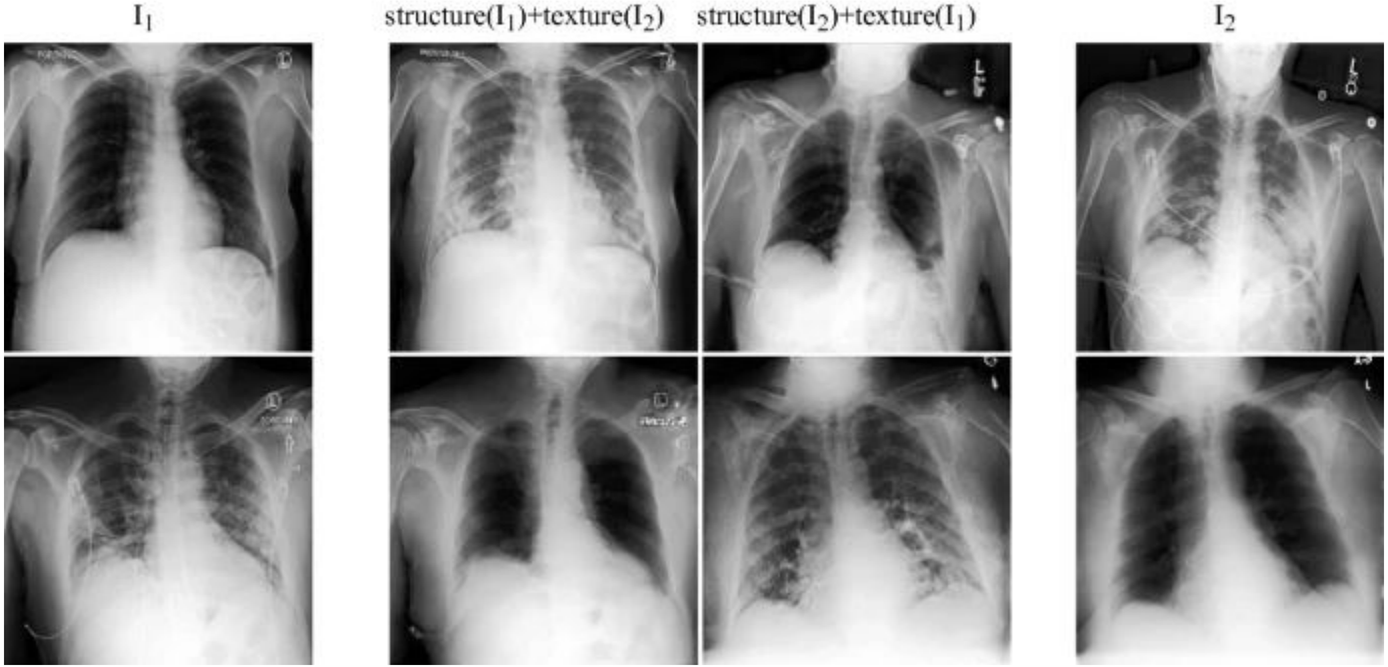
Lung Swapping AutoEncoder (LSAE)



1. Two sampled images: Image 1 and Image2
2. Encoded: (z1s , z1t) and (z2s , z2t)
3. Swapped: (z1s , z2t)
4. Decoded: Image hybrid

https://github.com/cvlab-stonybrook/LSAE/raw/main/assets/final_pipeline.png

Lung Swapping AutoEncoder (LSAE)



https://media.springernature.com/lw690/springer-static/image/chp%3A10.1007%2F978-3-030-87234-2_33/MediaObjects/521402_1_En_33_Fig1_HTML.png?as=webp

Experimental Design and Results

Dataset

1. ChestX-ray14
   - medical imaging dataset which comprises 112,120 frontal-view X-ray images of 30,805 (collected from the year of 1992 to 2015) unique patients with the text-mined fourteen common disease labels [1]
   - training (~70%), validation (~10%), and testing (~20%) [2]
2. COVOC
   - multi-institutional COVID-19 outcome prediction dataset, 340 CXRs from 327 COVID-19 patients
   - labeled based upon whether the patient required mechanical ventilation

1. https://paperswithcode.com/dataset/chestx-ray14

2. Zhou, Chest Radiograph Disentanglement for COVID-19 Outcome Prediction, 2020

Implementation

- decoder and discriminator architectures follow StyleGAN2
- encoders are built with residual blocks
- optimized by Adam
- PyTorch 1.7

```python
import math
from packaging import version

import torch
from torch import nn
from torch.nn import functional as F

from stylegan2.model import StyledConv, Blur, EqualLinear, EqualConv2d, ScaledLeakyReLU
from stylegan2.op import FusedLeakyReLU

from models.resnet import resnet50

class EqualConvTranspose2d(nn.Module):
    def __init__(
        self, in_channel, out_channel, kernel_size, stride=1, padding=0, bias=True
    ):
        super().__init__()

        self.weight = nn.Parameter(
            torch.randn(in_channel, out_channel, kernel_size, kernel_size)
        )
        self.scale = 1 / math.sqrt(in_channel * kernel_size ** 2)

        self.stride = stride
        self.padding = padding

        if bias:
            self.bias = nn.Parameter(torch.zeros(out_channel))
```

Semantic Prediction in CXRs by Texture Encoder 1

Method	Masked SIFID ↓	mIoU ↑	Pixel Acc ↑	Dice ↑
Init	0.0335	0.60	0.82	0.72
SAE	0.0257	0.76	0.91	0.85
LSAE	**0.0245**	**0.91**	**0.97**	**0.95**

Pre-train	Method	Params	mAUC ↑
Sup	CXR14-R50[24]	23M	0.745
	ChestNet [23]	60M	0.781
	CheXNet* [16]	7M	0.789
	Inception v3	22M	**0.796**
Unsup	Enc^t	**5M**	0.790

Semantic Prediction in CXRs by Texture Encoder 2

BER(%)↓	Inception v3	Enc^t in SAE	Enc^t in LSAE
split 1	20.25 ± 1.46	20.25 ± 1.63	19.00 ± 1.84
split 2	19.25 ± 3.67	20.50 ± 1.12	17.75 ± 1.66
split 3	17.75 ± 3.48	14.00 ± 1.85	12.75 ± 2.15
Avg	19.08	18.25	16.50

mAUC(%)↑	Inception v3	Enc^t in SAE	Enc^t in LSAE
split 1	85.45 ± 1.89	89.03 ± 2.16	89.17 ± 0.68
split 2	86.02 ± 1.27	85.63 ± 1.77	87.07 ± 1.91
split 3	89.12 ± 1.38	92.60 ± 1.25	95.00 ± 0.29
Avg	86.86	89.09	90.41

Personal Review and Take-Home Message

Personal Review

Strengths:

- Leverage the LSAE for data augmentation
- LSAE as a approach to disentangle chest CXRs into structure and texture representations

Weakness:

- GAN loss usage was not explained in fully manner
- Lack of comparison to other competitive methods

Take-Home Message

- LSAE to disentangle texture from structure
- Data augmentation technique
- Code is available on: https://github.com/cvlab-stonybrook/LSAE

Discussion

Thank you for your attention! Questions?