Presentation of Results

Diagnosis of Pathologies in Chest X-Ray Data

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September 29, 2020

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Dataset and Goal

- NIH Chest X-ray: over 100,000 Chest X-rays with multi-labels.
- 15 categories of lung diseases, so we used multi-hot encoding.
- Goal: Classify multiple pathology in the X-ray.

Figure: NIH Chest X-Ray

Data Augmentation

- Classical data augmentation
  - Crops, Rotation, Translation
- DCGAN data augmentation
  - batch size = 64
  - learning rate = 0.0002
  - Adam optimizer
  - Train 500 epochs separately for each category of disease (one at a time)

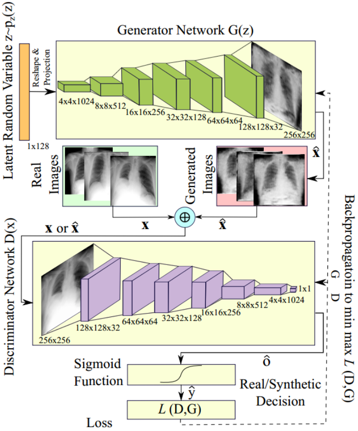
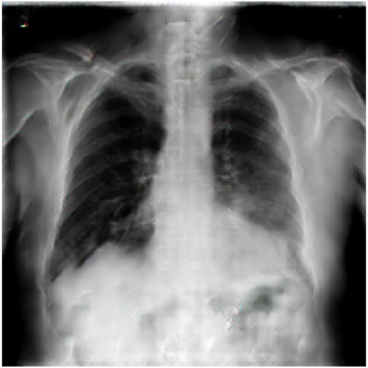


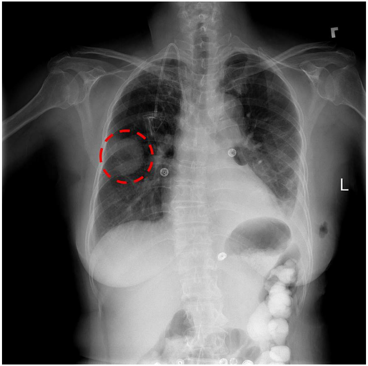
Figure: Architecture of DCGAN

Salehinejad et. al, Generalization of Deep Neural Networks for Chest Pathology Classification in X-Rays Using GAN, arXiv

DCGAN results



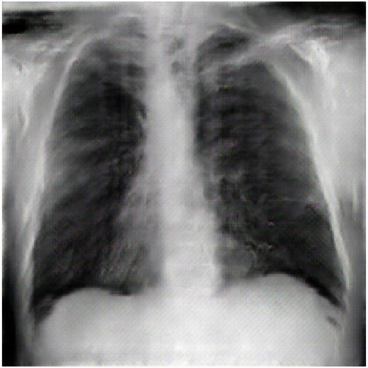
(a) DCGAN mass



(b) Original mass

Figure: Comparison of GAN synthetic and original images

DCGAN results



(a) DCGAN consolidation

(b) DCGAN consolidation

Figure: Unstable results of GAN synthetic images

Weighted Sampling

- Count: the occurrences of each label
- Inverse: the count to get each label's weight
- Sum: the label weights of each label collection
- Use weighted random sampler to draw batches in train loader

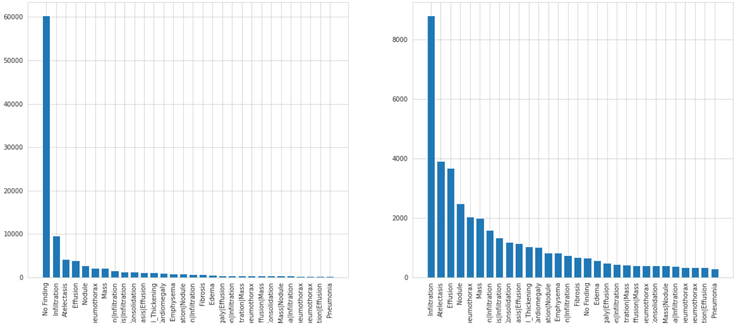


Figure: weighted sampling

Image Pre-processing and Segmentation

- Pre-processing using image processing techniques
- Feature Extraction
  - Traditional methods : GLCM, LBP
  - CNNs

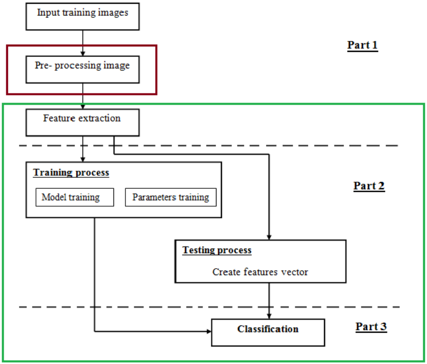


Figure: Image Feature Extraction Flow

The Long et al. (2016). Automatic Anthropometric System Development Using Machine Learning

Pre-processing

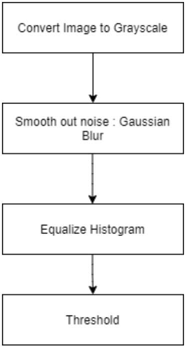


Figure: Preprocessing Image

Figure: Input Image

Figure: Thresholding

Segmentation

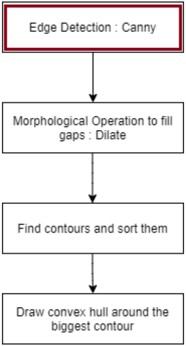


Figure: Canny Edge

Figure: Edge Detection

M. N. Saad et al, "Image segmentation for lung region in chest X-ray images using edge detection and morphology," 2014 IEEE

Segmentation

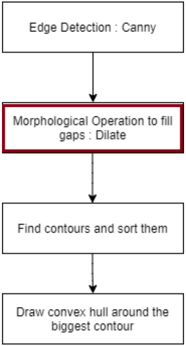


Figure: Morphological Operation

Figure: Dilate

Segmentation

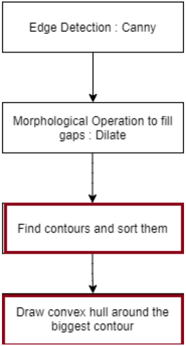


Figure: Finding Contours

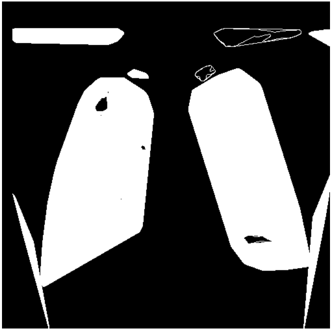


Figure: ROI Masks using Convex Hulls

Segmentation

Figure: Original Chest X-Ray

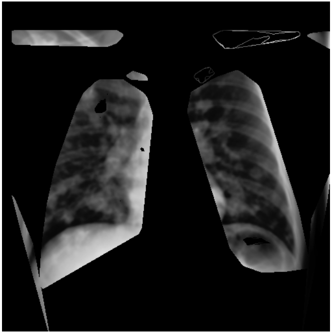


Figure: Lung ROI

Segmentation

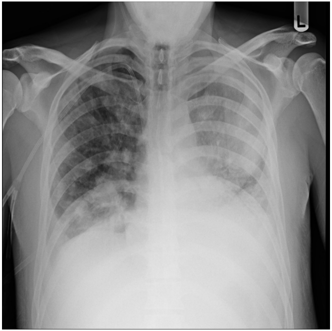


Figure: Original Chest X-Ray

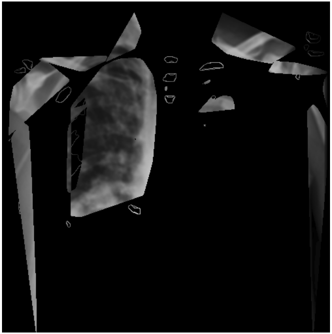


Figure: Incomplete Lung ROI

Transfer learning on ResNet18

- Pre-trained ResNet18 model
- Transfer learning process divided into 4 stages:
  - Stage1: 2 epochs
    - Training Layers: layer2, layer3, layer4, fc
  - Stage2: 1 epoch
    - Training Layers: layer3, layer4, fc
  - Stage3: 1 epoch
    - Training Layers: layer4, fc
  - Stage4: 1 epoch
    - Training Layers: fc - Linear, ReLU, Dropout, Linear

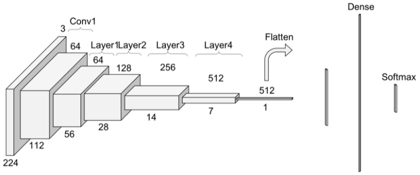


Figure: ResNet Architecture

Transfer learning on ResNet50

- Pre-trained ResNet50 model
- Transfer learning process divided into 4 stages:
  - Stage1: 2 epochs
    - Training Layers: layer2, layer3, layer4, fc
  - Stage2: 3 epochs
    - Training Layers: layer3, layer4, fc
  - Stage3: 3 epochs
    - Training Layers: layer4, fc
  - Stage4: 2 epochs
    - Training Layers: fc

Reference GitHub: n0obcoder/NIH-Chest-X-Rays-Multi-Label-Image-Classification-In-Pytorch

Presentation of Results for Different Networks

Images Used	Network	LR	Epochs	T Loss	V Loss
Original Image	ResNet18	0.01	30	2.178	2.177
Segmented Image	ResNet18	0.001	30	2.039	2.044
Original+Segmented Image	ResNet18	0.001	5	1.638	1.645
Original+DCGAN Image	ResNet50	0.001	10	1.724	1.727

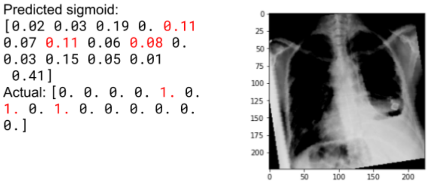


Figure: Classification example using Resnet 18 Model

- Initial Resnet 18 model.

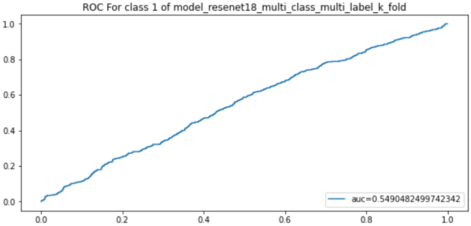


Figure: ROC Class 1 Initial Resnet 18

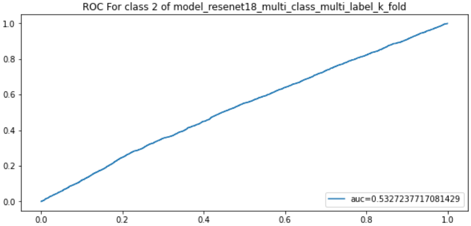


Figure: ROC Class 2 Initial Resnet 18

- Resnet 18 with Segmentation of images.

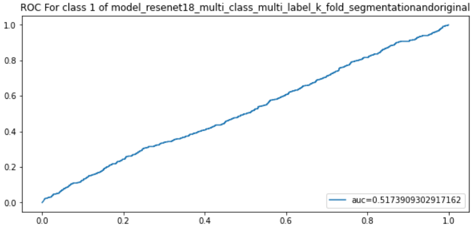


Figure: ROC Class 1 Resnet 18 with Segmentation

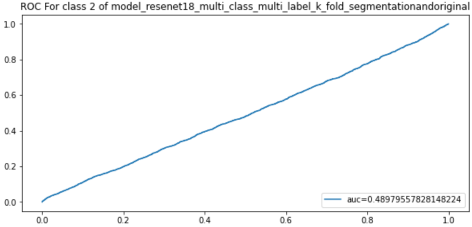


Figure: ROC Class 2 Resnet 18 with Segmentation

- Resnet 50 with added DCGAN Images.

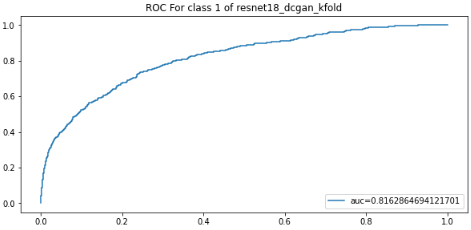


Figure: ROC Class 1 Resnet 50 with DCGAN

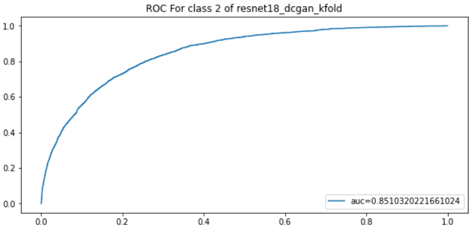


Figure: ROC Class 2 Resnet 50 with DCGAN

Original image Network

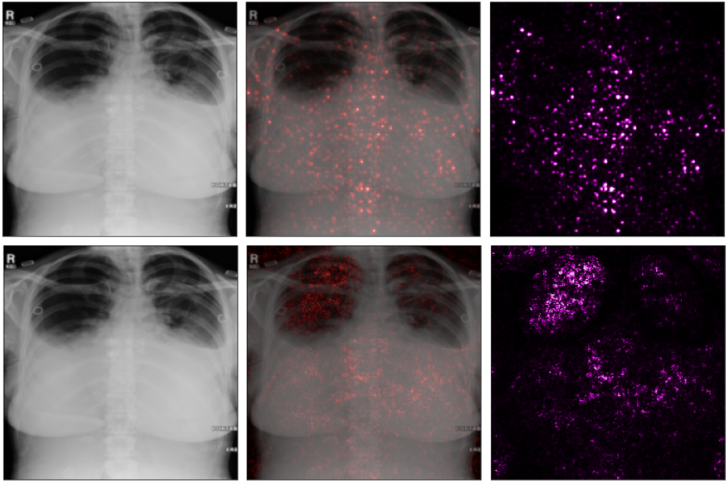


Figure: Original image correctly classified as Effusion. Upper images show Saliency, bottom images show GradientShap

Segmented image Network

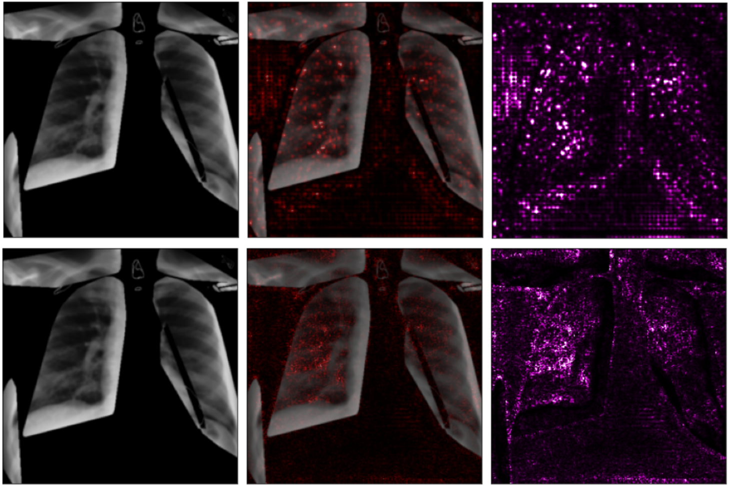


Figure: Segmented image wrongly classified with Effusion instead of no finding. Upper images show Saliency, bottom images show GradientShap

Segmented+Original image Network

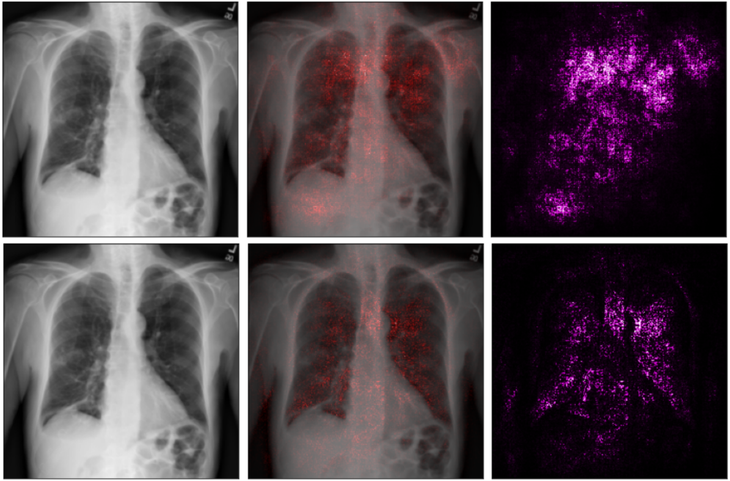


Figure: Original image wrongly classified with Emphysema instead of Atelectasis. Upper images show Saliency, bottom images show GradientShap

Segmented+Original image Network

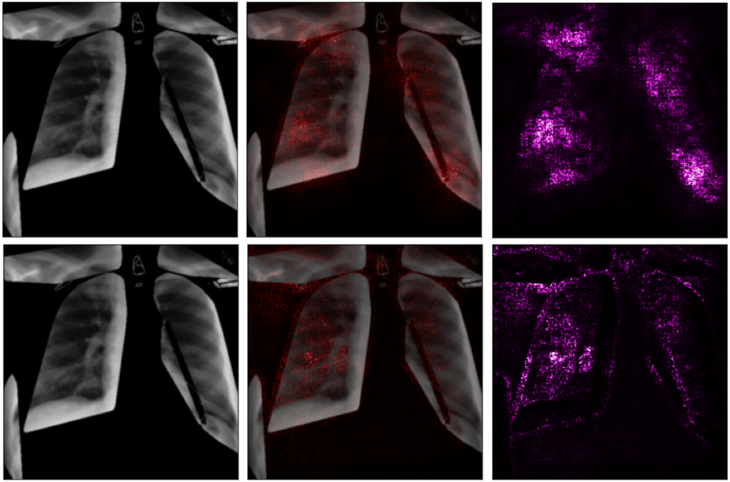


Figure: Segmented image correctly classified with no finding. Upper images show Saliency, bottom images show GradientShap

DCGAN+Original image Network

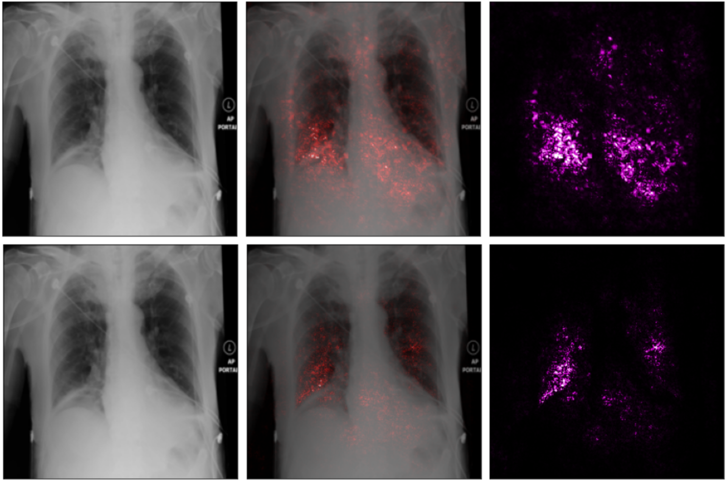


Figure: Original image correctly classified with Atelectasis. Upper images show Saliency, bottom images show GradientShap

DCGAN+Original image Network

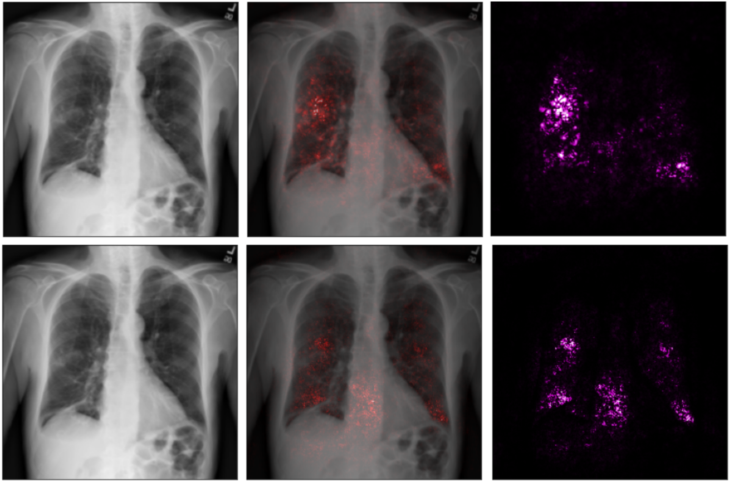


Figure: Original image wrongly classified as Effusion instead of Atelectasis. Upper images show Saliency, bottom images show GradientShap

Conclusion

- Conclusion
  - Our model achieved an average ROC AUC score of 0.85
  - We explored different combinations of models and data augmentation techniques
  - Hard to classify all 15 labels and multi-label
- Future improvements
  - GAN synthetic images need to be more stable and higher resolution
  - Stable segmentation with less information loss
  - Use 15 different classifiers
  - CNN parameters fine-tuning

Questions?