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Lung Segmentation from Chest X-rays using Variational Data Imputation

Presented at ICML Workshop on Learning from Missing Data (Artemiss 2020)

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Source Code & Models: https://github.com/raghavian/lungVAE $_{\rm Artemiss\,2020}$

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COVID-19 like diseases obfuscate lungs in chest X-rays



Contribution

Automatic segmentation of lungs in the presence of pulmonary opacifications by posing it as a *missing data* problem

Caption: Normal CXR shows lungs clearly whereas abnormal CXR has high opacity where the right lung is hardly seen. Brighter regions are tissue-like as they attenuate X-rays whereas darker regions indicate presence of air, in this case inside the lungs.



Slide 2 — Raghavendra Selvan — Lung Segmentation from Chest X-rays using Variational Data Imputation — Artemiss 2020

Proposed segmentation model uses variational data imputation



Extensive augmentation

During training extensive data augmentation is used to simulate lung opacifications.

Captions: (left) The proposed model with variational encoder for data imputation, $V_{\phi}(\cdot)$, U-net type segmentation network with encoder $E_{\theta}(\cdot)$, decoder $D_{\psi}(\cdot)$. (right) Chest X-rays with and without augmentation. (a) No augmentation (b) With block masking (c) With diffused noise marked with red ellipses (d) Test image with high opacity



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Experiments & Results

- Public CXR datasets (Shenzhen and Montgomery hospitals)
- o Training: 528 CXRs, Validation: 176 CXRs
- Test set. 30 CXRs from diverse datasets with manual annotations (in-house experts)
- U-net model for baseline comparison
- Ablation of different augmentation strategies

Table 1. Performance	measures on t	he test set
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Models	Augmentation	Dice Overlap	Accuracy
Baseline	Standard	0.7335 ± 0.17	0.8449 ± 0.09
Proposed	Standard	0.7204 ± 0.18	0.8392 ± 0.10
Baseline	Block	0.7563 ± 0.15	0.8522 ± 0.09
Proposed	Block	0.7688 ± 0.17	0.8552 ± 0.10
Baseline	Diffuse	0.7757 ± 0.15	0.8654 ± 0.10
Proposed	Diffuse	0.7965 ± 0.11	0.8652 ± 0.11
Baseline	Block+Diffuse	0.8173 ± 0.12	0.8654 ± 0.11
Proposed	Block+Diffuse	$\textbf{0.8503} \pm \textbf{0.07}$	$\textbf{0.8815} \pm \textbf{0.11}$



a) Three test set samples with highest and least dice accuracy for both methods (rows 1 & 2) along with an input CXR with additional variations in pose (row-3). b) baseline model predictions, c) proposed model predictions and d) the ground truth. Both predictions are for models trained with block and diffused noise.

Green: True positive, Blue: False Negative, Red: False Positive

