Deep Learning in Medical Imaging

Rongguang Wang

Electrical and Systems Engineering
University of Pennsylvania
rgw@seas.upenn.edu

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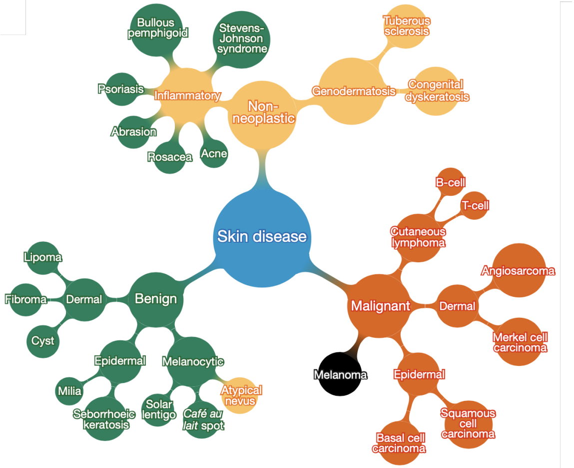
Skin Cancer Classification



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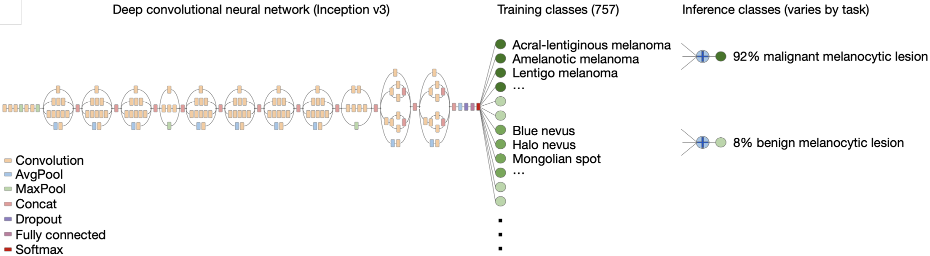

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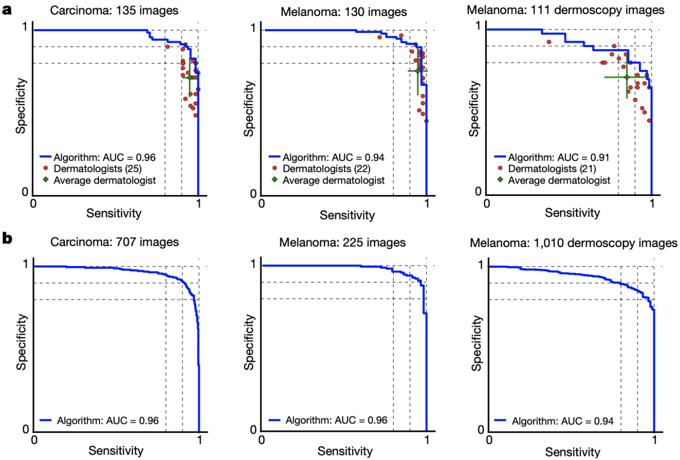

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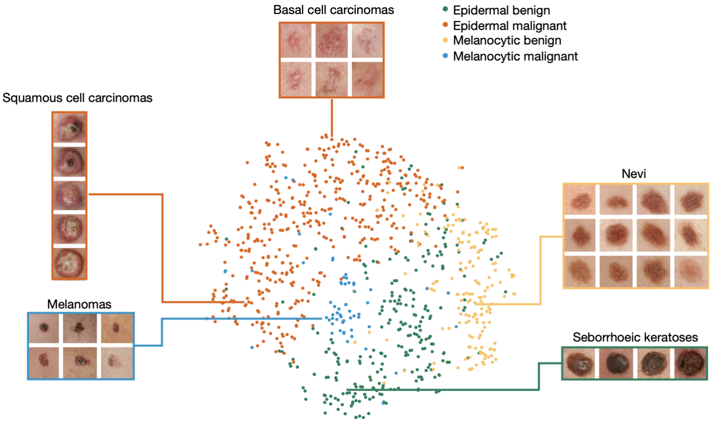

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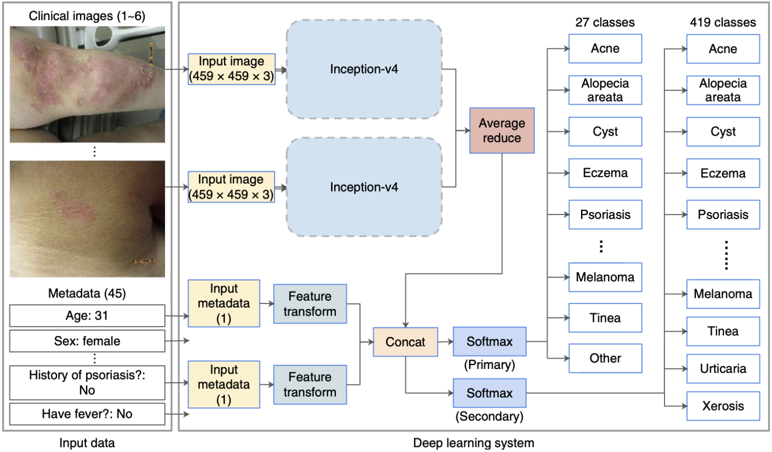
Skin Disease Diagnosis



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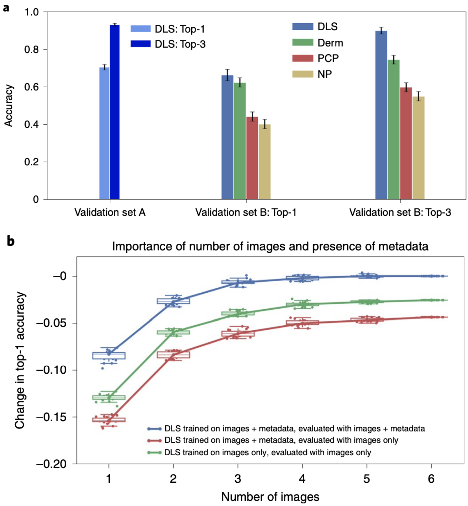
Skin Disease Diagnosis



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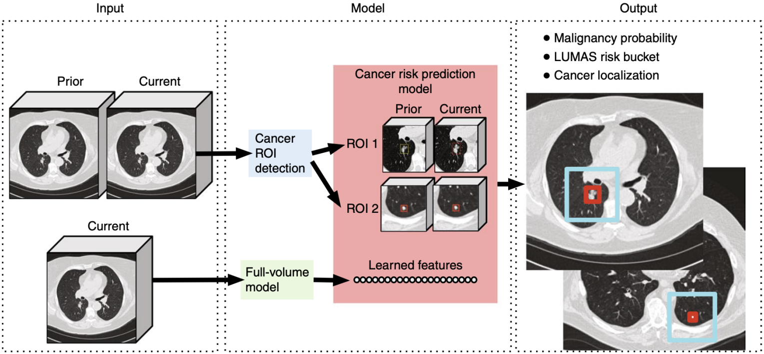
Lung Cancer Screening



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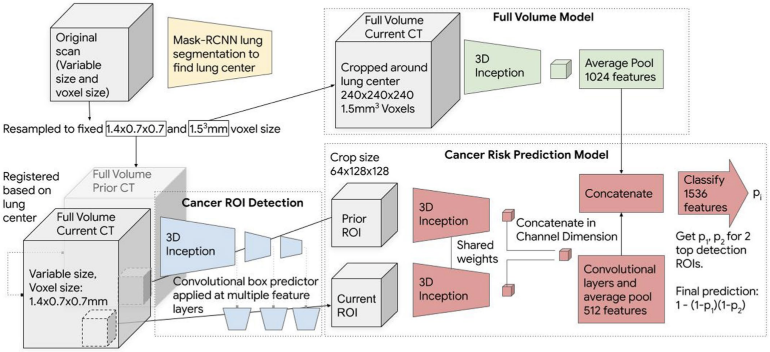

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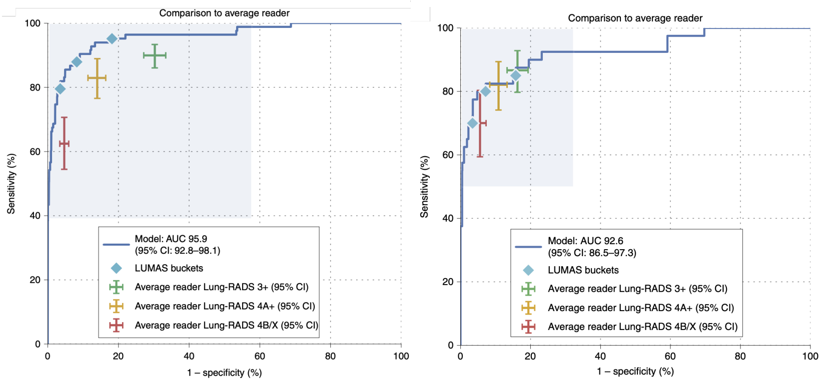

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Uncertainty Estimation

- What kind of uncertainty quantification questions might make sense for ML-based clinical diagnosis?
- Would any of the techniques that we studied in class be applicable?
- Would one need to develop some new techniques?

Batch Effects Correction

$$Y^*_{ijk} = \frac{Y_{ijk} - f_k(X_{ij}) - g_{ik}}{d_{ik}} + f_k(X_{ij}), \tag{1}$$

where X_{ijk} are the covariates and Y_{ijk} is the ROI volume for site i, subject j, and region k; g_{ik} denotes the estimated location effect, and d_{ik} represents the estimated scale effect.

- Linear

$$f_k(X_{ij}) = a_k + X_{ij} \cdot b_k; \tag{2}$$

- Generalized Additive Model (GAM)

$$f_k(x_{ij}, z_{ij}) = a_k + f(x_{ij}) + b_k \cdot z_{ij}, \tag{3}$$

where x_{ij} and z_{ij} are age and gender separately.

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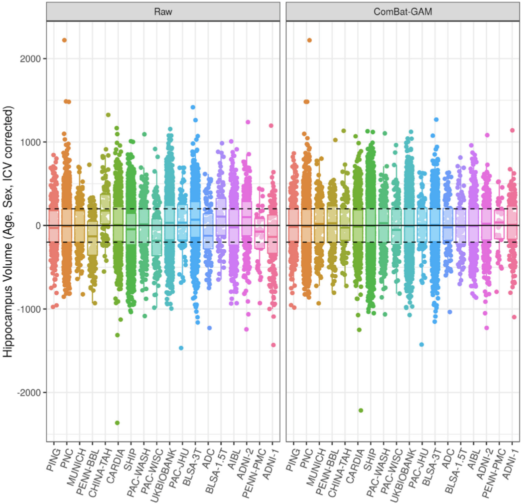
Harmonization



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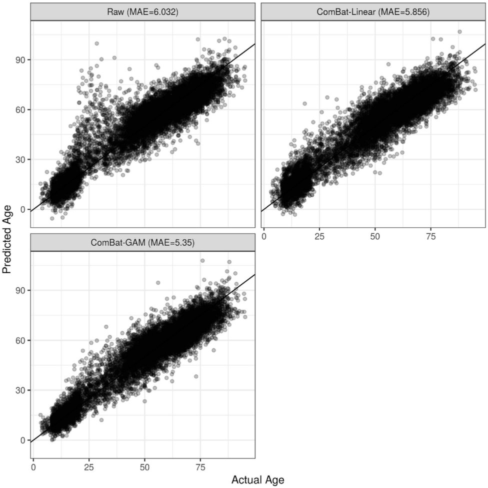

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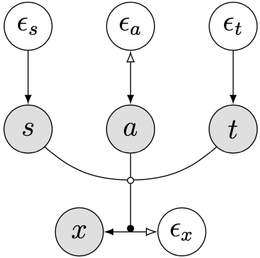
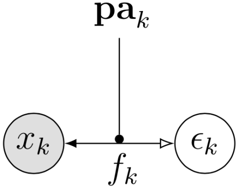


$$
\begin{aligned}
s &:= \epsilon_S, & \epsilon_S &\sim \mathsf{Ber}(p_\theta^S);\\
a &:= f_A(\epsilon_A) = (\mathsf{Exp} \circ \mathsf{Affine} \circ \mathsf{Spline}_\theta)(\epsilon_A), & \epsilon_A &\sim \mathcal{N}(0,1);\\
t &:= \epsilon_T, & \epsilon_T &\sim \mathsf{Cat}(K, p_\theta^T);\\
x &:= f_X(\epsilon_X; s, a, t) = (\mathsf{ConditionalTransform}_\theta([s,a,t]))(\epsilon_X), & \epsilon_X &\sim \mathcal{N}(0,1).
\end{aligned}
$$

R Wang et al. "Harmonization with flow-based causal inference". In: *International Conference on Medical Image Computing and Computer-Assisted Intervention*. 2021, pp. 181–190

Structural Causal Model

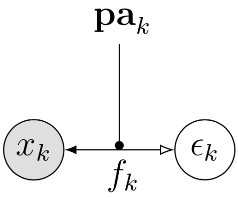


$$\mathcal{M} := (\boldsymbol{S}, P(\boldsymbol{\epsilon}))$$

- $\boldsymbol{S} = (f_1, \cdots, f_K)$ of structural assignments $x_k := f_k(\epsilon_k; \boldsymbol{pa}_k)$, where $\boldsymbol{pa}_k$ is the set of parents (direct causes) of x_k;
- $P(\boldsymbol{\epsilon}) = \prod_{k=1}^{K} P(\epsilon_k)$ over mutually independent exogenous noises $\boldsymbol{\epsilon}$.

$$P_{\mathcal{M}}(\boldsymbol{x}) = \prod_{k=1}^{K} P_{\mathcal{M}}(x_k | \boldsymbol{pa}_k)$$

Counterfactual Inference



- Abduction: inferring the posterior noise distribution $P_{\mathcal{M}}(\boldsymbol{\epsilon}|\boldsymbol{x}) = \prod_{k=1}^{K} P_{\mathcal{M}}(\epsilon_k|x_k, \boldsymbol{pa}_k)$;
- Intervention: replacing the structural assignment(s) which result in a modified SCM $\tilde{\mathcal{M}} = \mathcal{M}_{\boldsymbol{x};do(\tilde{x}_k)} = (\tilde{\boldsymbol{S}}, P_{\mathcal{M}}(\boldsymbol{\epsilon}|\boldsymbol{x}))$;
- Prediction: sampling from the distribution $P_{\tilde{\mathcal{M}}}(\boldsymbol{x})$ entailed by the modified SCM.

Harmonization

Algorithm Harmonization with flow-based SCM.

Initialize: flow parameters $\theta = \{\phi, \psi\}$ and learning rate α
for each training iteration i **do**
    $(x^i, \boldsymbol{pa}^i_X) \in (x, \boldsymbol{pa}_X)$
    $\mathcal{L}(\theta) = \log p_\psi(f_\phi^{-1}(x^i; \boldsymbol{pa}^i_X)) - \log|\det J_{f_\phi^{-1}}(x^i; \boldsymbol{pa}^i_X)|$
    $\theta \leftarrow \theta - \alpha \nabla_\theta \mathcal{L}(\theta)$
end for
Inference: $P_{\mathcal{M}}(\boldsymbol{\epsilon}|\boldsymbol{x}) = \prod_{k=1}^{K} p_\psi(f_\phi^{-1}(x_k), \boldsymbol{pa}_k)$
Action $do(\cdot)$: $x_k := \tilde{x}_k$ or $x_k := \tilde{f}_k(\epsilon_k; \tilde{\boldsymbol{pa}}_k)$
Sampling: $\boldsymbol{x}^h \sim P_{\tilde{\mathcal{M}}}(\boldsymbol{x})$ where $\tilde{\mathcal{M}} = (\tilde{\boldsymbol{S}}, P_{\mathcal{M}}(\boldsymbol{\epsilon}|\boldsymbol{x}))$
Return: $\boldsymbol{x}^h$

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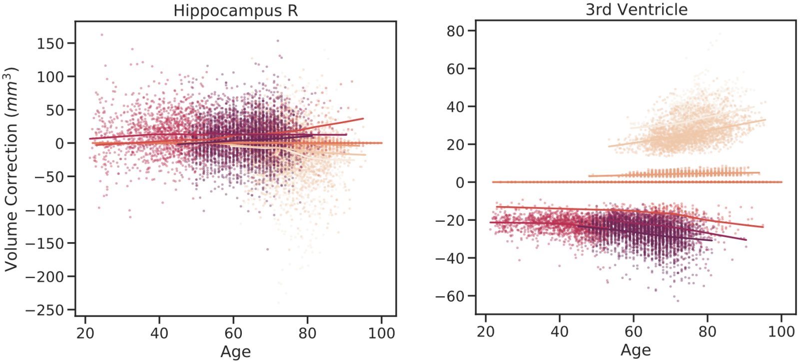
Harmonization



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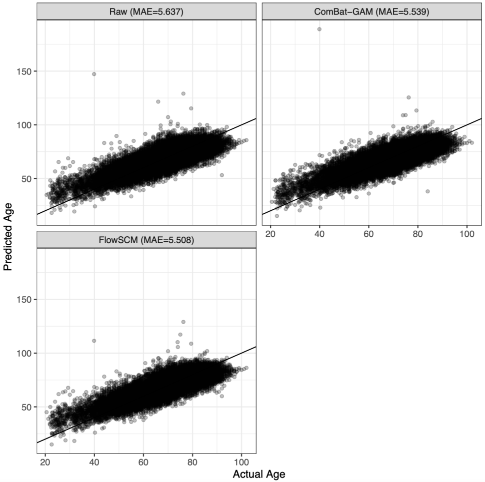

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