

Bridging the Gap: From Post Hoc Explanations to Inherently Interpretable Models for Medical Imaging

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TLDR: Extracting a mixture of interpretable models from a BlackBox to provide instance specific concept-based explanations using First-order logic (FOL).

Post hoc explanation

Pros

Does not alter the Black box.

Cons

- Inconsistent explanations.
- No recourse.

Interpretable by design

Pros

Support concept intervention.

Cons

- Harder to train.
- Sub par performance.

Each color denotes an expert

How to blur this gap?

Desirable properties

- Does compromise the performance.
- Can be intervened to fix the misclassification

Design choices

- Carve interpretable models from Blackbox.
- Concept based
- First order logic for concept interaction

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Assumption Route Interpret Repeat Fix Φ , update h \mathcal{X} thin ears DOB shortened muzzle $\Phi \circ h^2$ $\Phi \circ h^1$ $\Phi \circ h^3$ Residual (r^3) $\Phi \circ h^0$ round feet Residual (r^1) Residual (r^0) Residual (r^2) Carve out interpretable models from Black box **Blackbox Model** Symbolic Model Selector Each g is E-LEN [Barberio et al.], constructing FOL * SelectiveNet [Geifman et al.] optimization

Extract concepts from MIMIC-CXR using Radgraph NLP pipeline



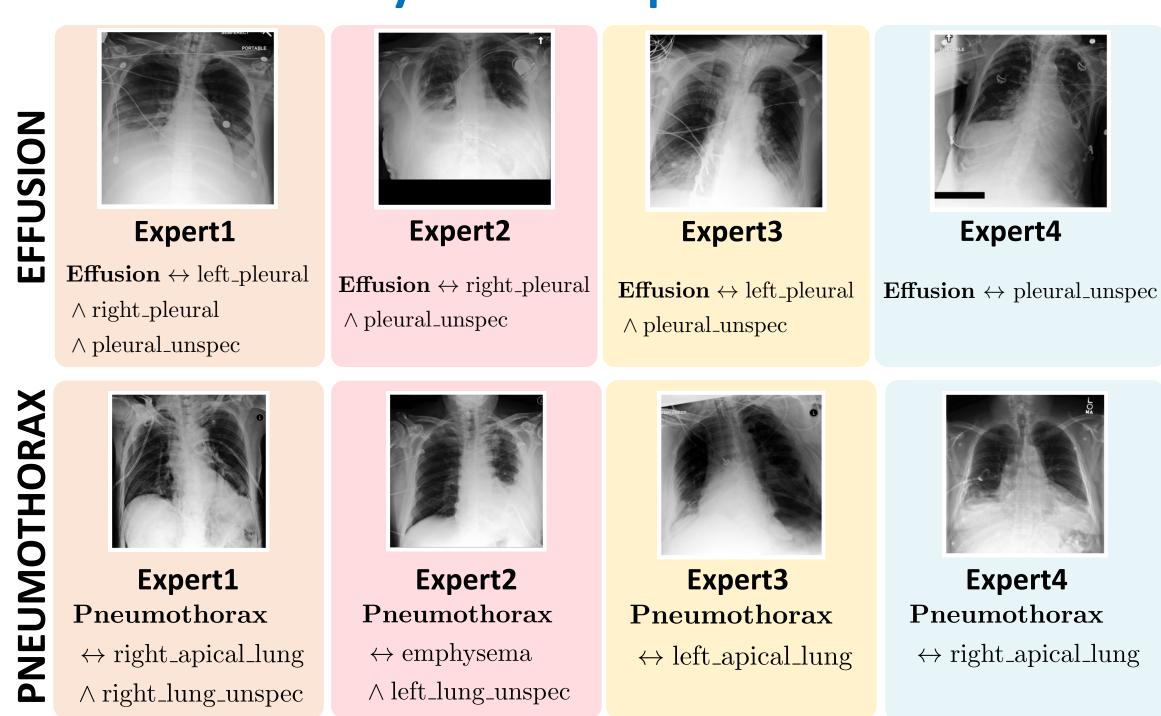
Ke Yu et al.

Report:

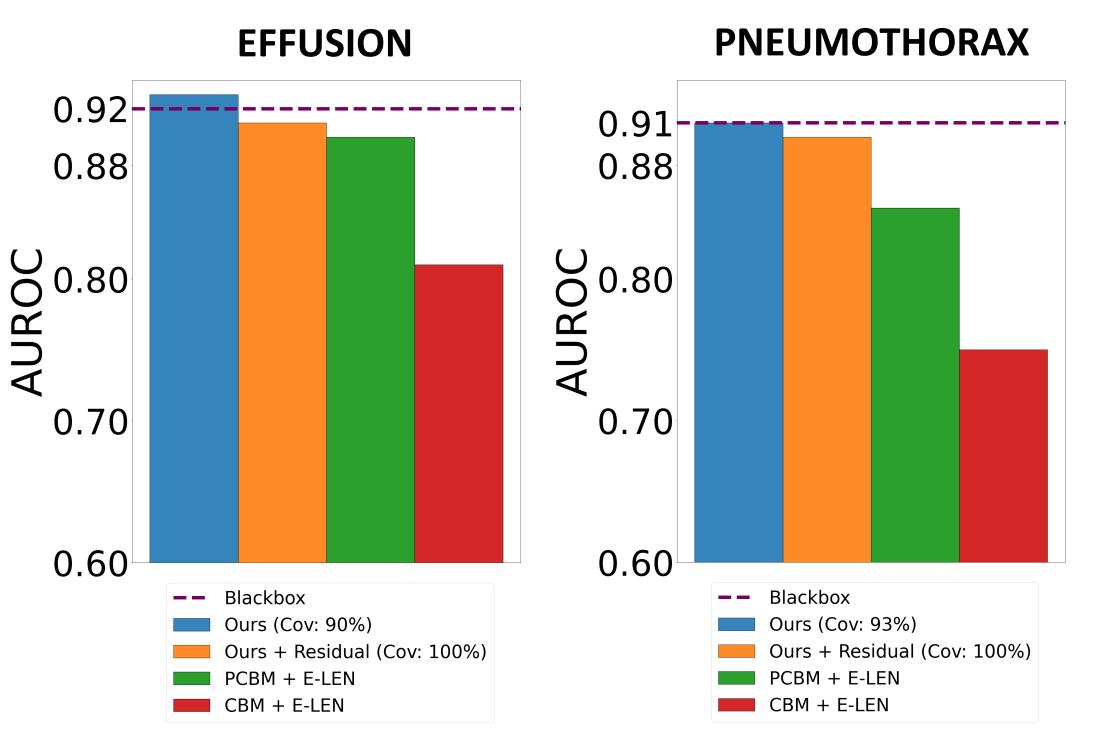
Right upper lobe **consolidation** with adjacent. While this may be infectious in nature, a CT scan is recommended for further clarification.

Diversity in local explanations

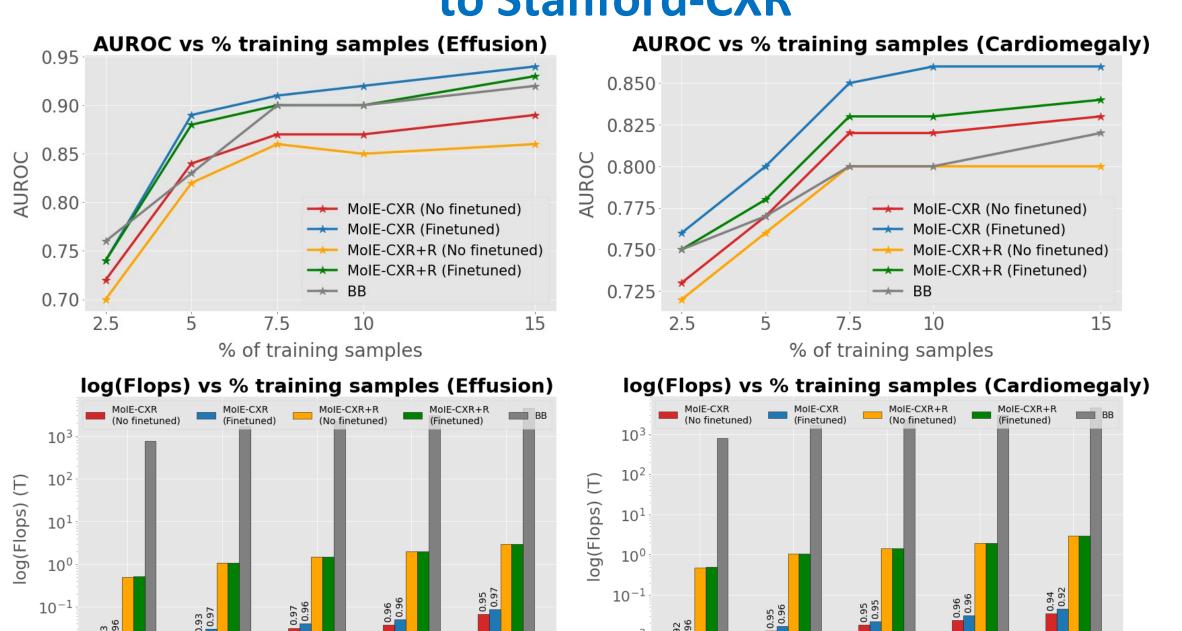
* Continue till at least 90% samples covered



Not compromising the accuracy in MIMIC-CXR



Transferring the first 3 experts of MIMIC-CXR to Stanford-CXR



2.5

% of training samples

 10^{-2}

% of training samples

log(Flops) (T)