LOCALIZATION AND LABELING OF POSTERIOR RIBS IN CHEST RADIOGRAPHS USING A CRF-REGULARIZED FCN WITH LOCAL REFINEMENT

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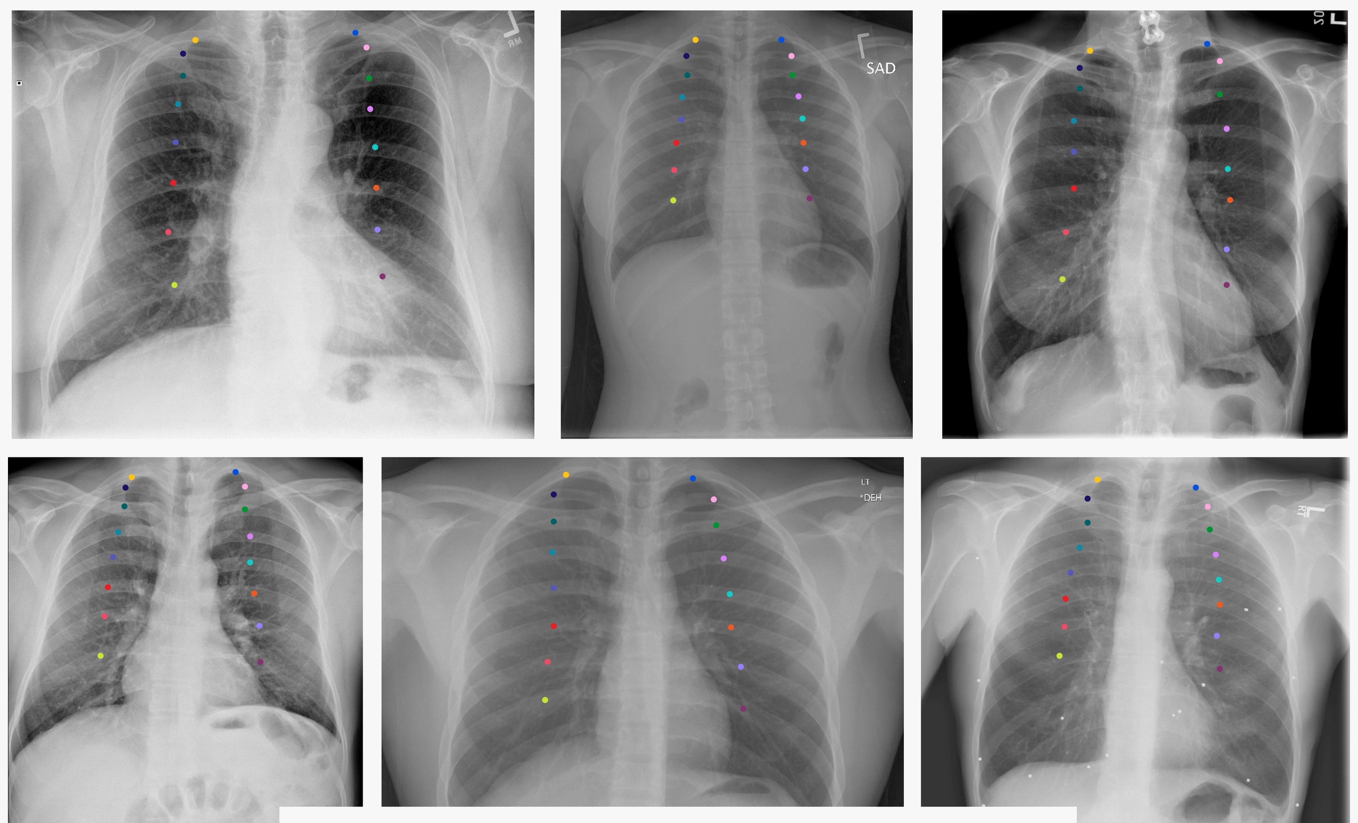
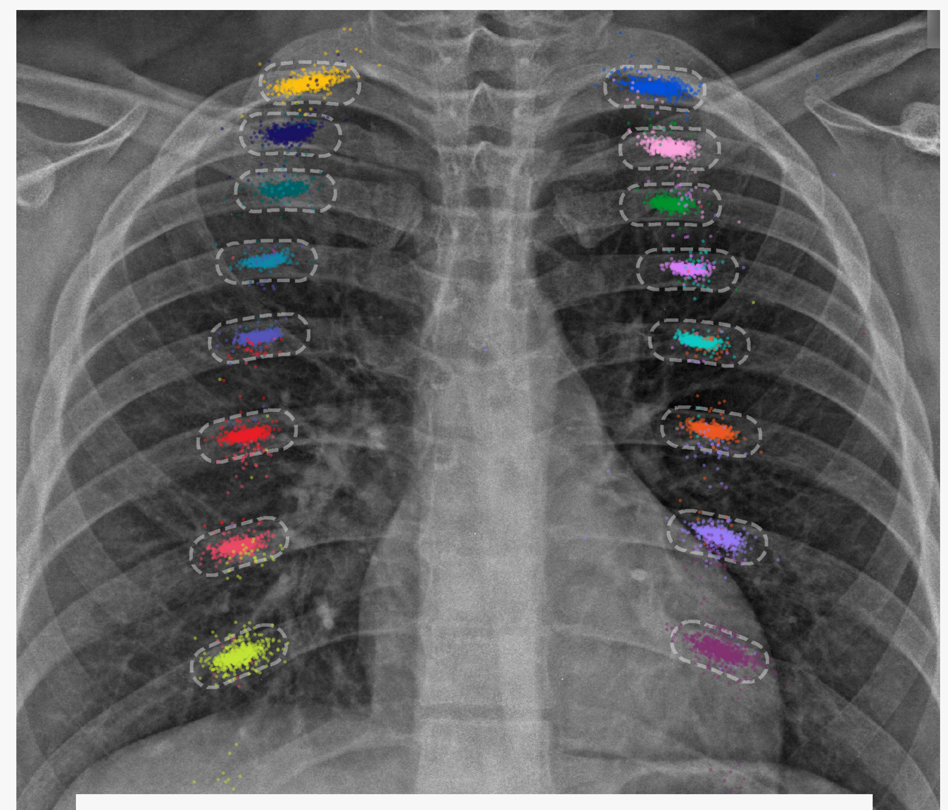
ABSTRACT

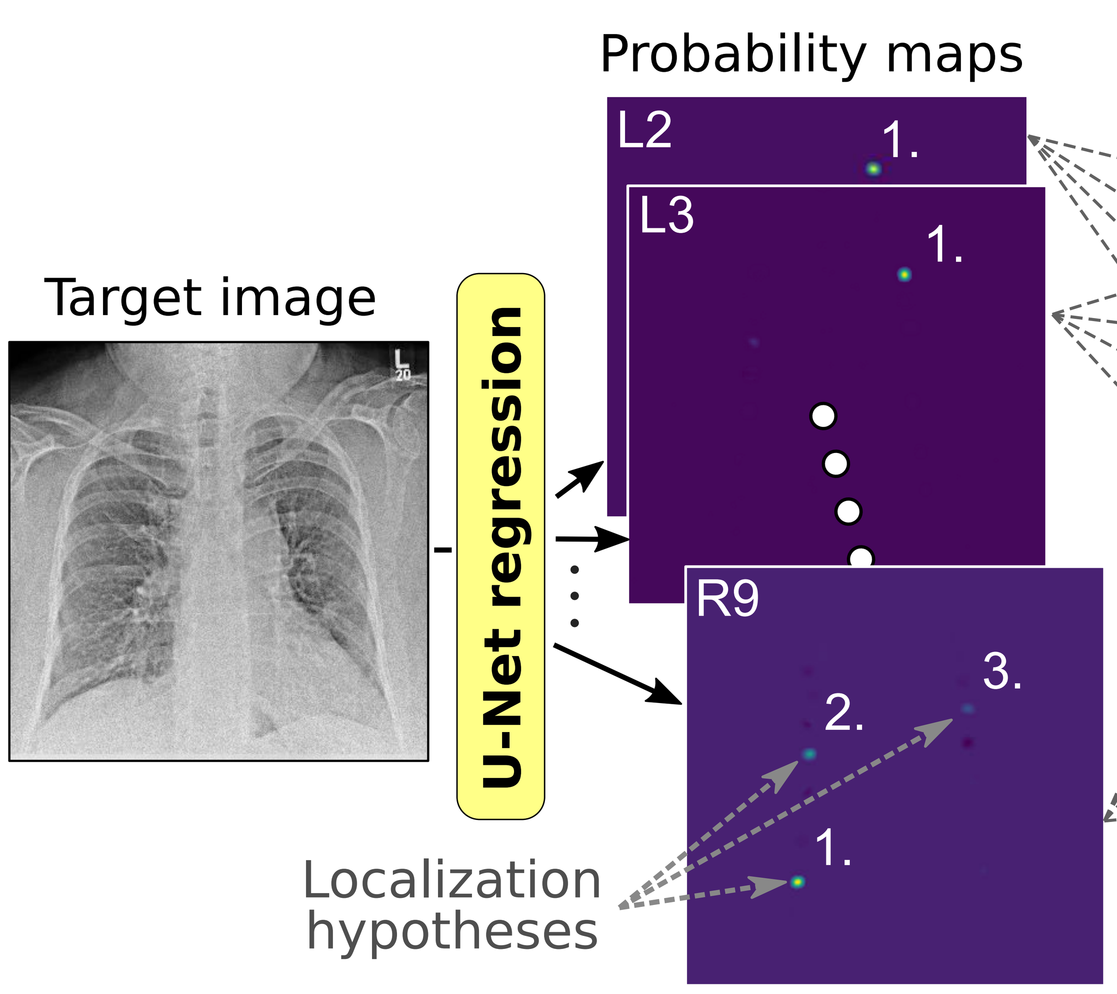
We propose a **general approach for localizing spatially correlated landmarks** using a combination of a **fully convolutional network** (FCN) as hypotheses generator and a **conditional random field** (CRF) as spatial regularizer. To overcome potentially incorrect hypotheses, we introduce a **third refinement step** based on a **novel "refine" label** introduced in the CRF. We use our method to **solve the detection of posterior ribs**, achieving a **success rate of 94.6%** on the public Indiana chest X-ray collection.


83.0% fully correct cases


94.6% correct landmarks

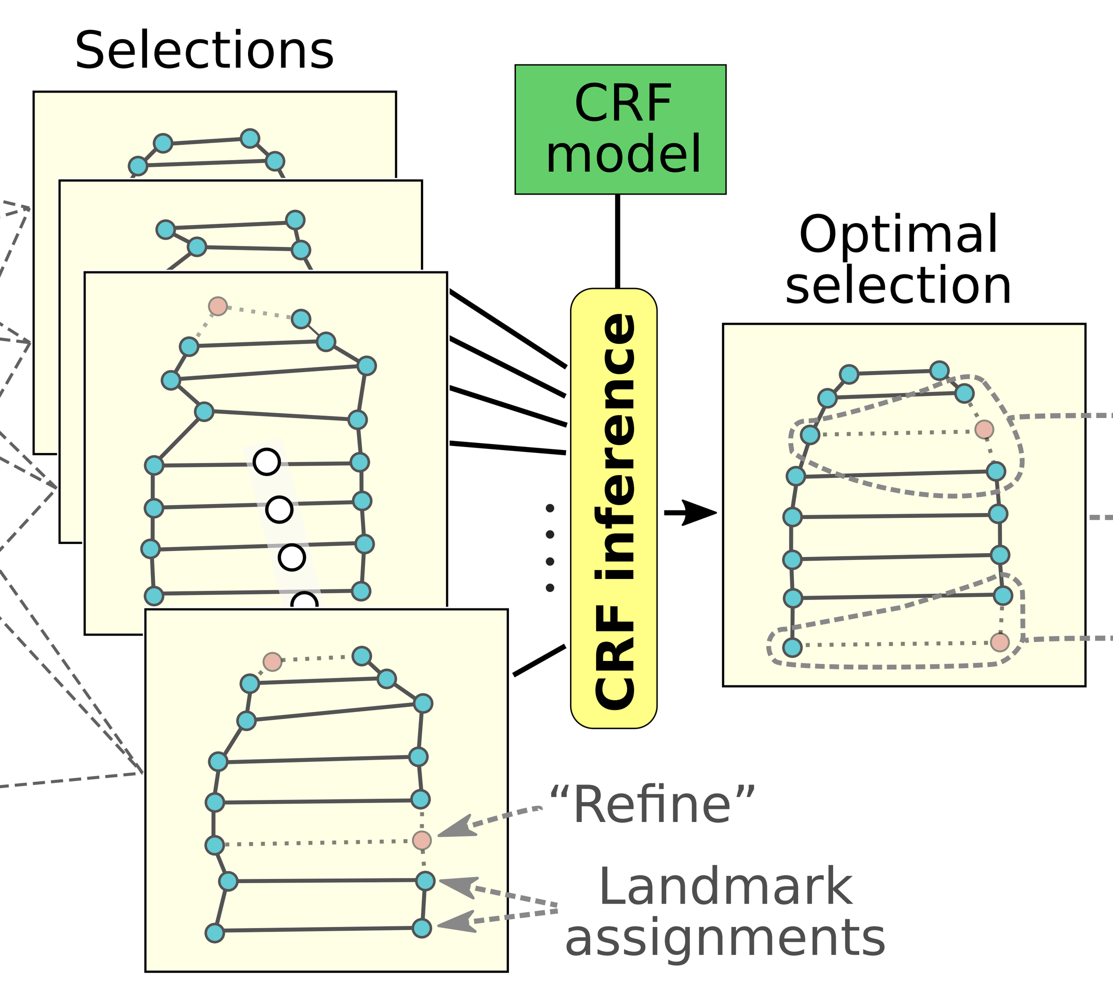
METHOD

1. Use U-Net to generate **localization hypotheses**



- Drop soft-max layer of U-Net to regress heatmaps (instead of classification)
- Sum-squared-error loss with Gaussian at true positions as target
- Use non-maximum suppression to extract 15 localization hypotheses from each regressed heatmap
- **One network to handle all landmarks at the same time (36ms)**
- But poor accuracy on its own with just 30.7% fully correct cases

2. Use CRF to **assign position or "refine"** to each landmark



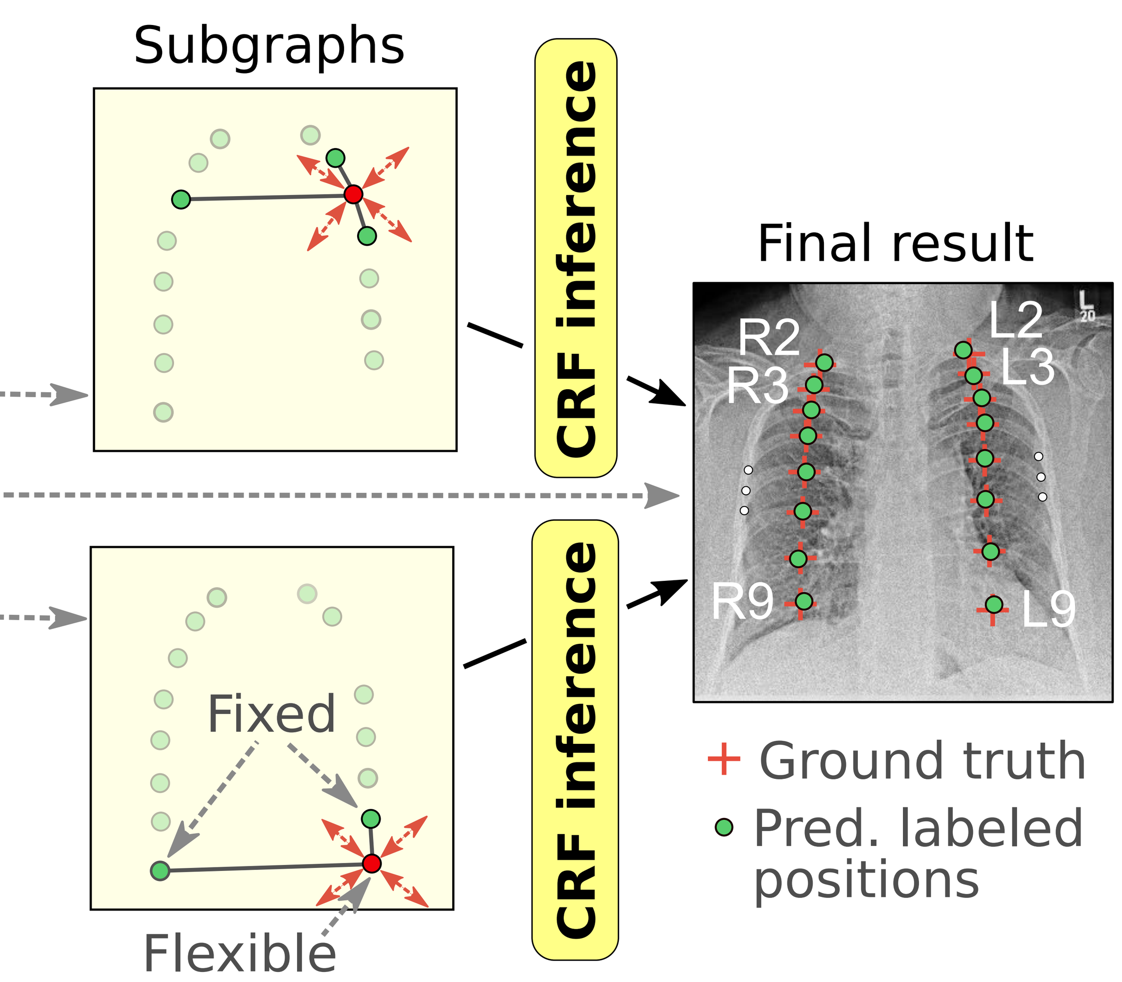
- Landmarks as CRF nodes and localization hypotheses plus novel "refine" label as states
- Unary potentials set to heatmaps
- Binary potentials assess spatial relations: angle, distance, vector
- **Potential weights and "refine" energies are learned from data:**

$$E(\mathbf{S}) = \sum_j \lambda_j \cdot \begin{cases} \beta_j & \exists i \in \mathrm{Scope}(\phi_j)\ s_i = \mathrm{refine} \\ \phi_j(\mathbf{S}) & \end{cases}$$

$$L(\boldsymbol{\lambda}, \boldsymbol{\beta}) = \frac{1}{K} \sum_k \max\left(0, m + E(\mathbf{S}_k^+) - E(\mathbf{S}_k^-)\right)$$

- CRF inference (61ms) increases fully correct cases to 57.3% (+26.6%)

3. Refine selected landmarks over all image pixels



- Extract small subgraphs around "refine"-labeled nodes
- Fix locations for all subgraph nodes except the "refine" node
- Perform CRF inference over all positions instead of 15 hypotheses
- **Sub-problem is feasible $O(n)$ in contrast to full problem $O(n^N)$**
- Greedy heuristic determines order
- Refinement (73ms) increases **fully correct cases to 83.0%** (+25.7%)

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