Deep Learning Feature Based Medical Image Retrieval for Large-Scale Datasets

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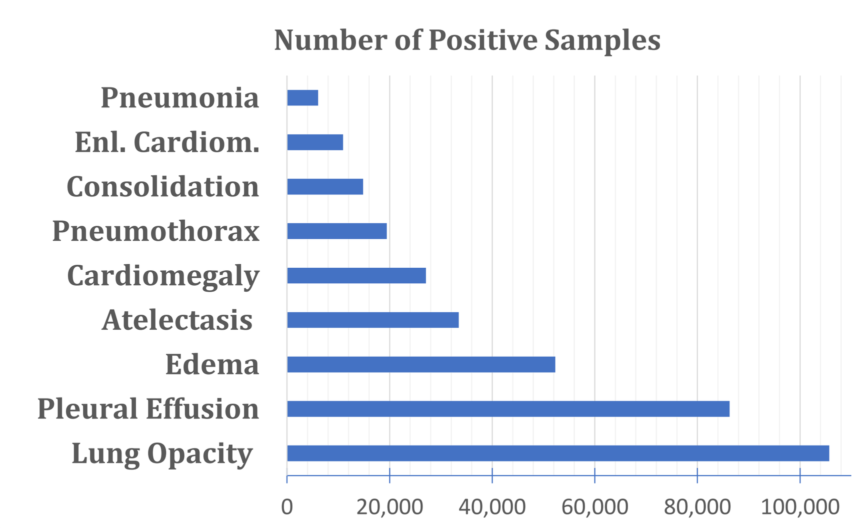
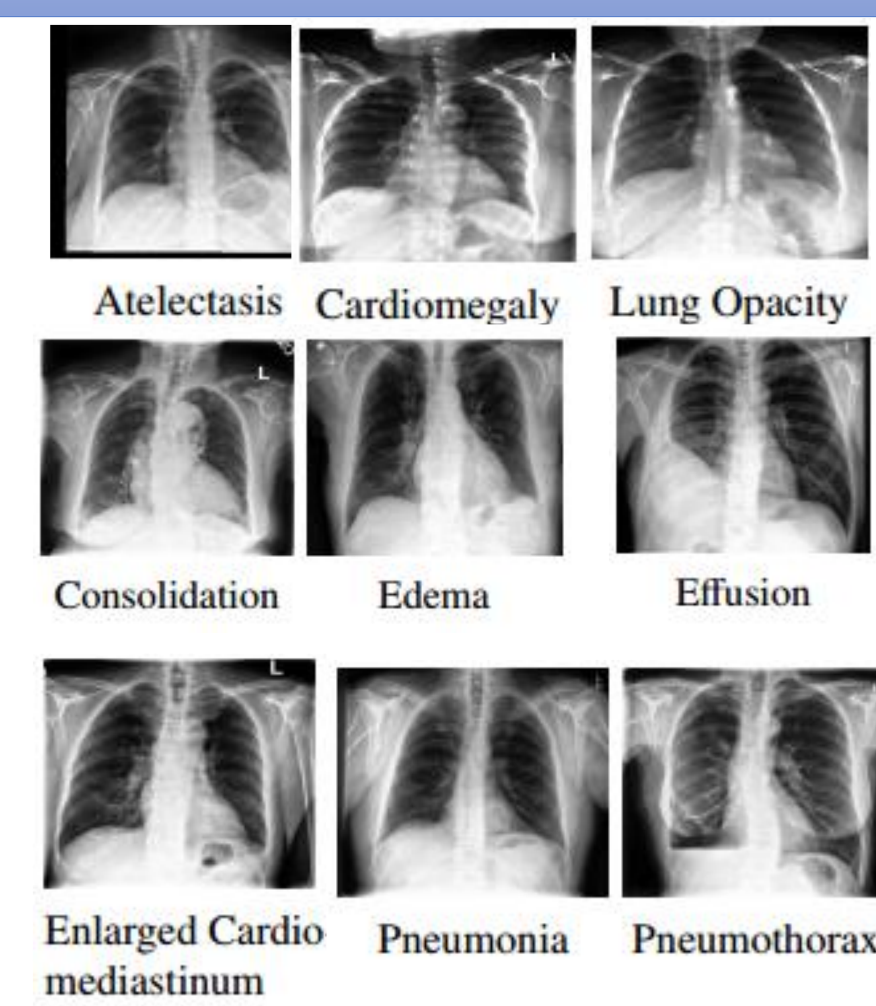
Motivation

- With the hike in the number of radiology examinations ordered, there is a substantial surge in the radiologists' workloads, resulting in a longer radiology turnaround time [1] .
- A computer-assisted system to automatically extract previously diagnosed radiographs with similar image-content can be a helpful tool to guide the diagnosis accelerating the radiologists' workflow and thereby improving the overall quality healthcare [2].
- Medical images are more difficult to analyze compared to generic images, owing to the complex imaging parameters, interactions between different diseases, and subtle differences between images with different diagnosis [3].

Dataset

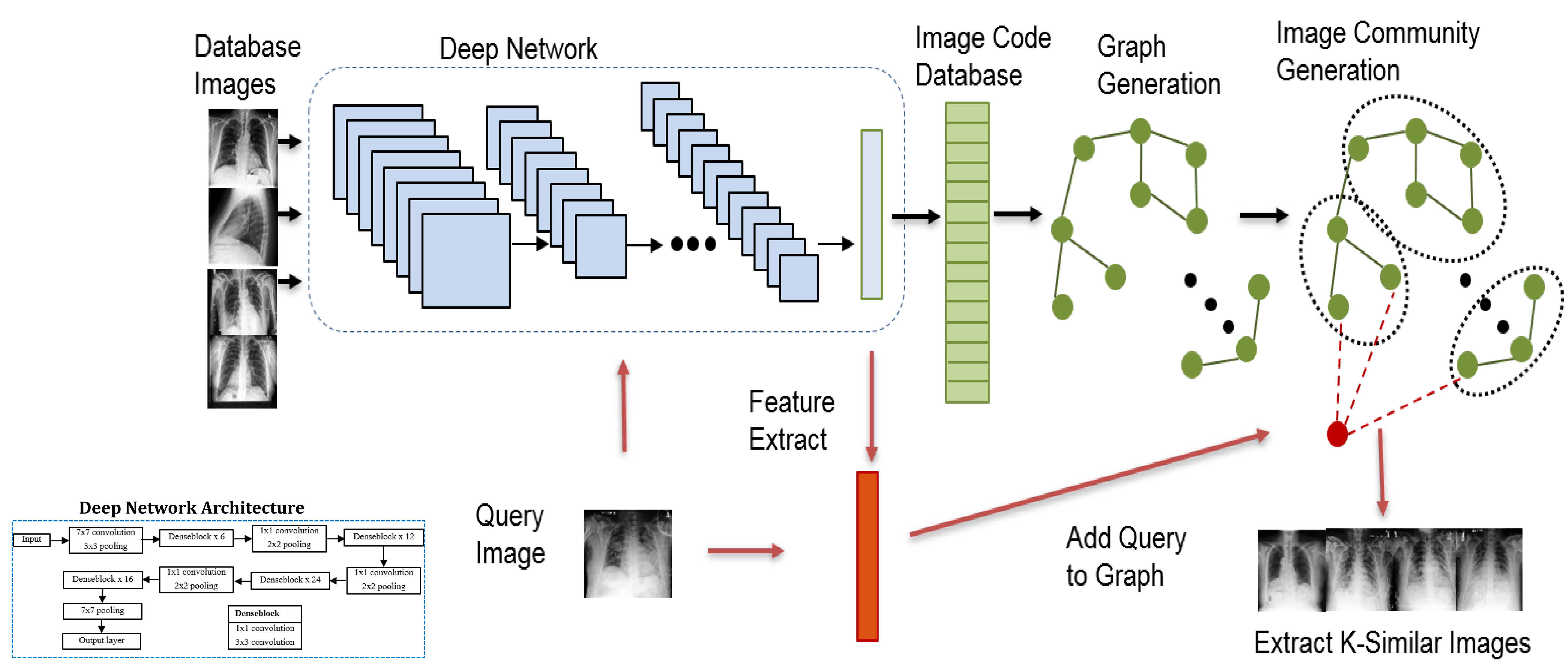
- Large-scale chest X-ray dataset [4]
- 223,648 chest X-ray images
- 191,229 frontal and 32,419 lateral
- 64,740 subjects
- Nine disease labels





Framework

- Deep learning model based image code generator to eliminate the need for manual feature selection and to benefit from a large dataset
- A prior clustering technique[5] to extract similar image subspace offline
- A region growing based approach to extract similar images given a query image
- Deep learning model trained on the dataset



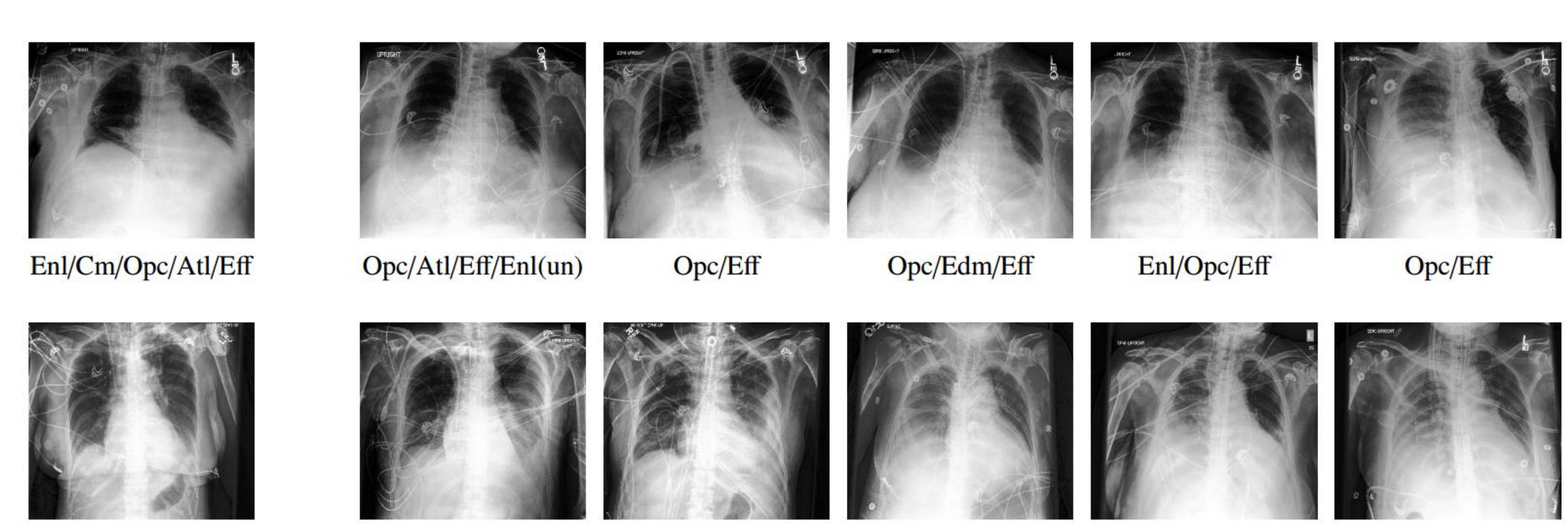
Algorithm

Algorithm 1 Top-K similar image retrieval for a query image, I

1: **Input :** Graph $\mathcal{G}$, Edge generating function function E, Database $\{I_f, i_f, C(I_f)\}$, Query image I, Number of images to retrieve K
2: Add I to $\mathcal{G}$ with edges $E(I, I_f)$
3: Set region $R = I_f$
4: **while** $|R| < K$ **do**
5: Select cluster c, associated database image set I_c s.t. maximum weighted modularity is achieved when R is assigned to c^{th}-cluster
6: **for** $j = 1, 2, .., min(|I_c|, K)$ **do**
7: Select I_u s.t. $I_u = \arg\max_{I_j} \Delta q(I, I_j); I_j \in I_c, I_j \notin R$ and $C(I_j) = c$
8: Add I_u to R
9: **end for**
10: **end while**

Results

Dataset	ACG	Precision
With five most prevalent diseases	0.54	78%
With all diseases labels	0.37	73%
ACG = $\sum_{n=1}^{K} r_n / K$; r_n=graded relevance at position-n ;	Precision = #similar image/#total images retrieved	



Query **Retrieved Images**

Opc:Lung Opacity, Eff:Pleural Effusion, Enl:Enlarged Cardiomediastinum, Atl:Atelectasis, Edm:Edema, Cons:Consolidation, un: uncertain

Comparison

Method	AvG
Lan *et al.* [6]	0.31
Chen *et al.* [7]	0.42
Our Approach	0.57
AvG = $\sum_{n=1}^{K} s_n / K$; s_n=common labels shared between query and retrieved image at position-n	

Future Works

- Incorporating clinical information in the retrieval system
- Combined supervised image code generation and clustering

References

[1] Bastawrous,S. *et al.* (2017), Jrnl. of Digtl. Img. 30:309–313. **[2]** Akgul,C.B. *et al.* (2011), Jrnl. of Digtl. Img. 24:208–222. **[3]** Li, Z. *et al.*(2018), Med.Img.Analys.43:66-84. **[4]** Irvin J. *et al.* arXiv: 1901.07031, 2019. **[5]** Haq,N.F. *et al.* (2019), Patten Recog., 122:14–22. **[6]** Lan R. *et al.* (2018), Mult.Tools.Appl. 77(9):10853:10866. **[7]** Chen Z. *et al.* (2018), MICCAI, 620-628.