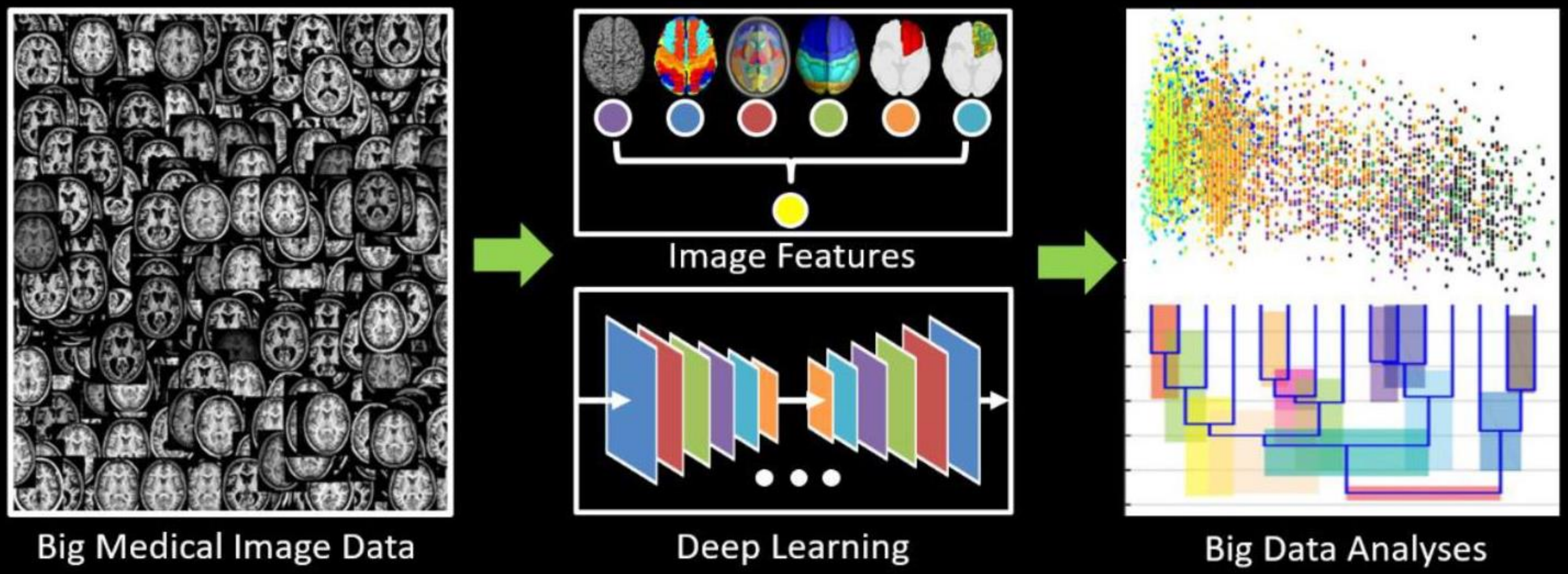


Image Retrieval and Active Learning

[Spring 2020 CS-8395 Deep Learning in Medical Image Computing]

Instructor: Yuankai Huo, Ph.D.
Department of Electrical Engineering and Computer Science
Vanderbilt University

Image Retrieval

https://lukeoakdenrayner.wordpress.com/2017/12/18/the-chestxray14-dataset-problems/

Atelectasis

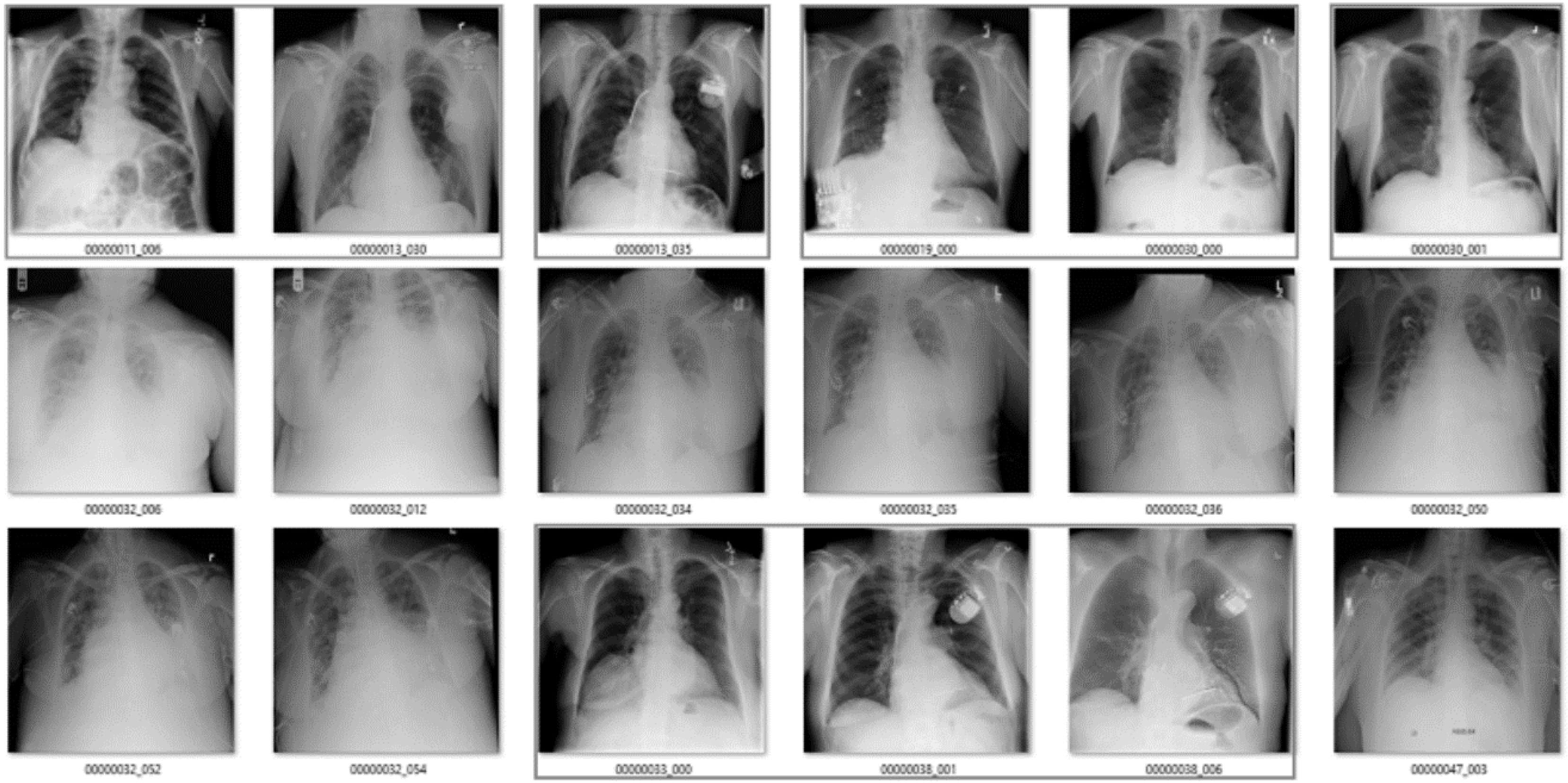
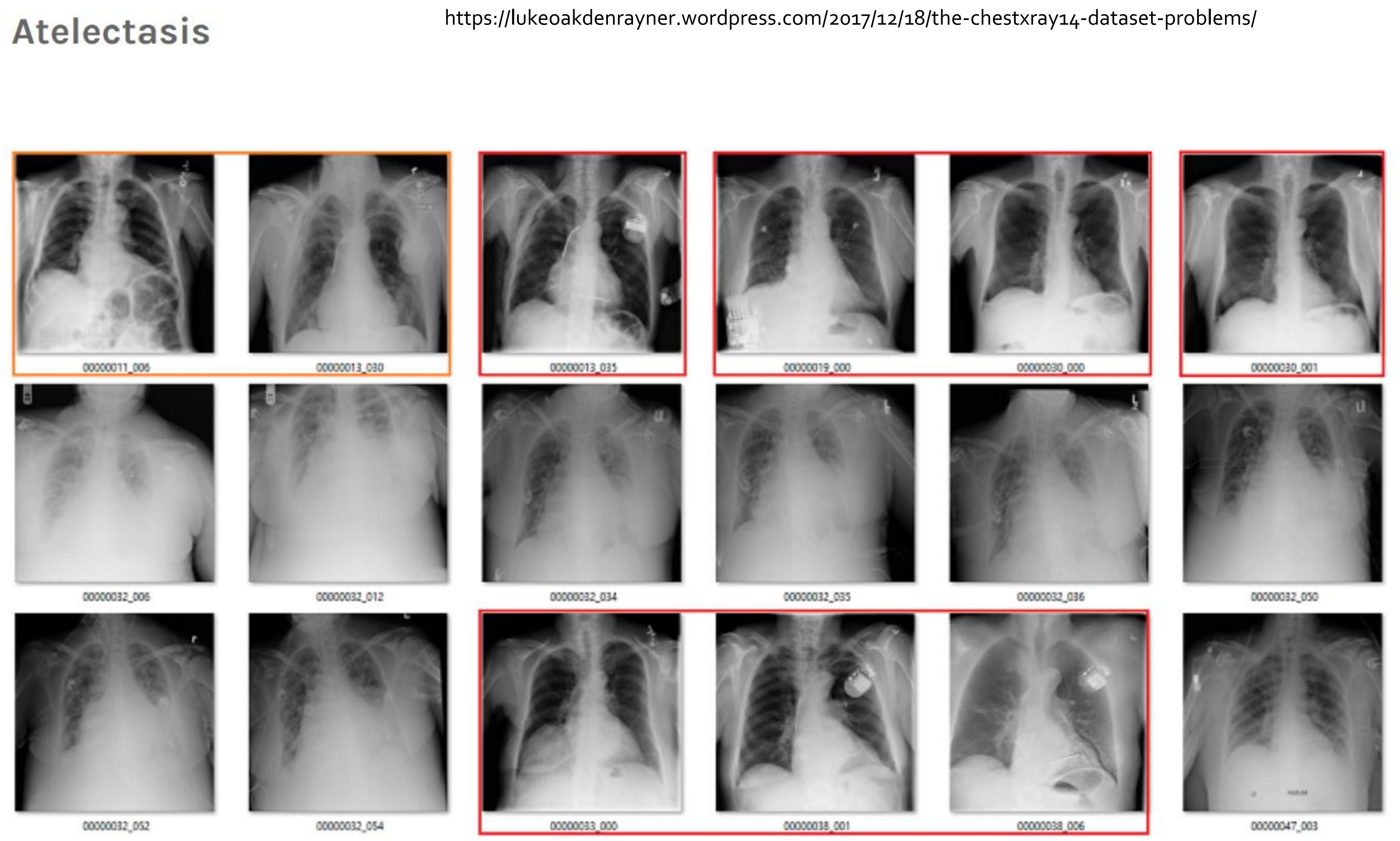


Image Retrieval

https://lukeoakdenrayner.wordpress.com/2017/12/18/the-chestxray14-dataset-problems/



Active Learning

https://lukeoakdenrayner.wordpress.com/2017/12/18/the-chestxray14-dataset-problems/

Atelectasis

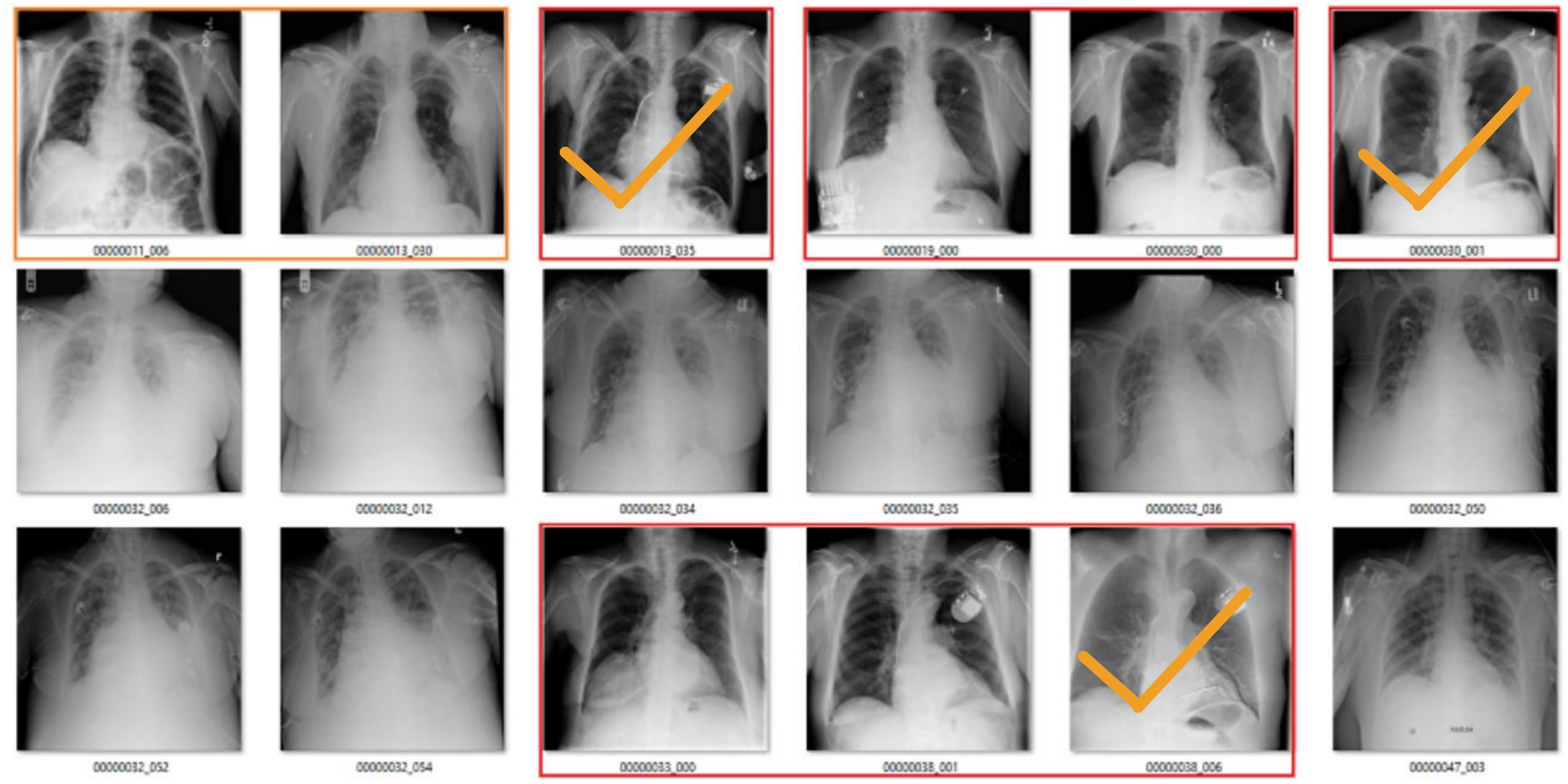


Image Retrieval

Image Retrieval

Concept-based Image Retrieval

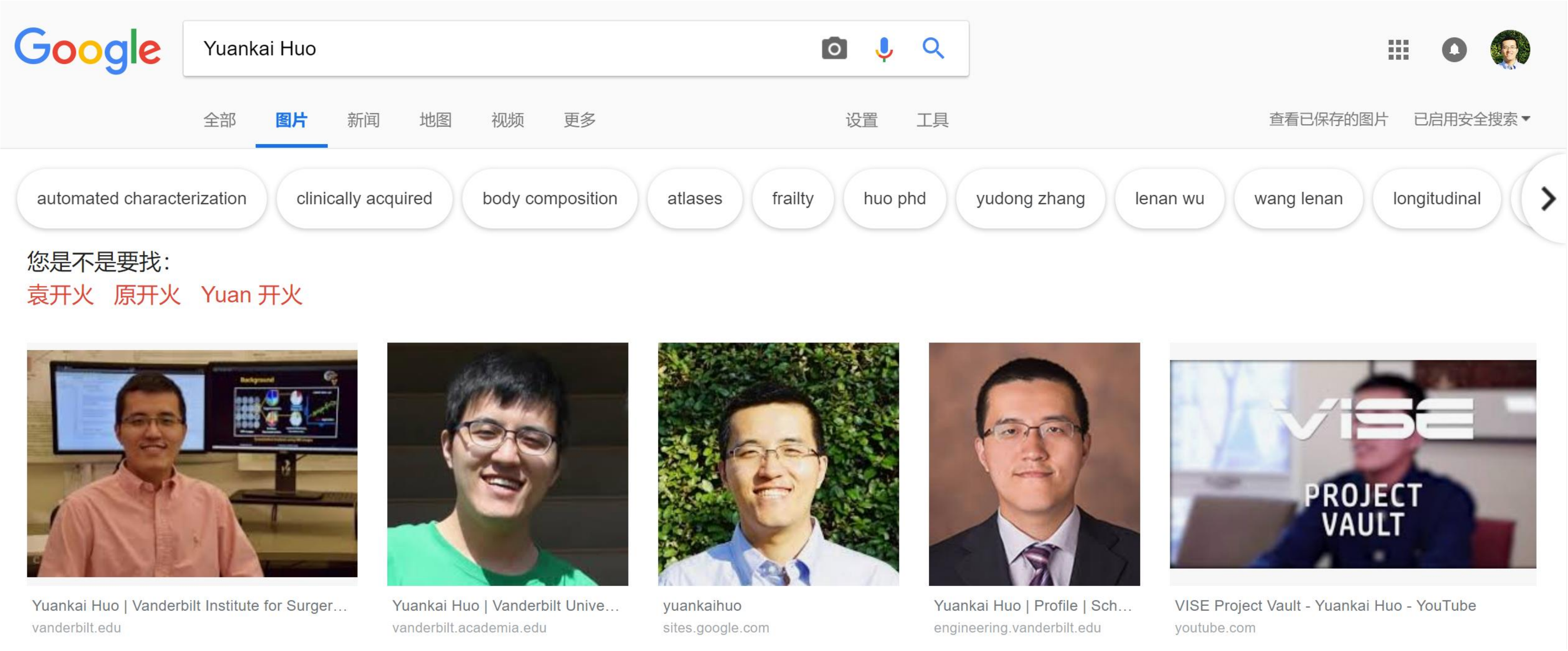
Content-based Image Retrieval

Classification

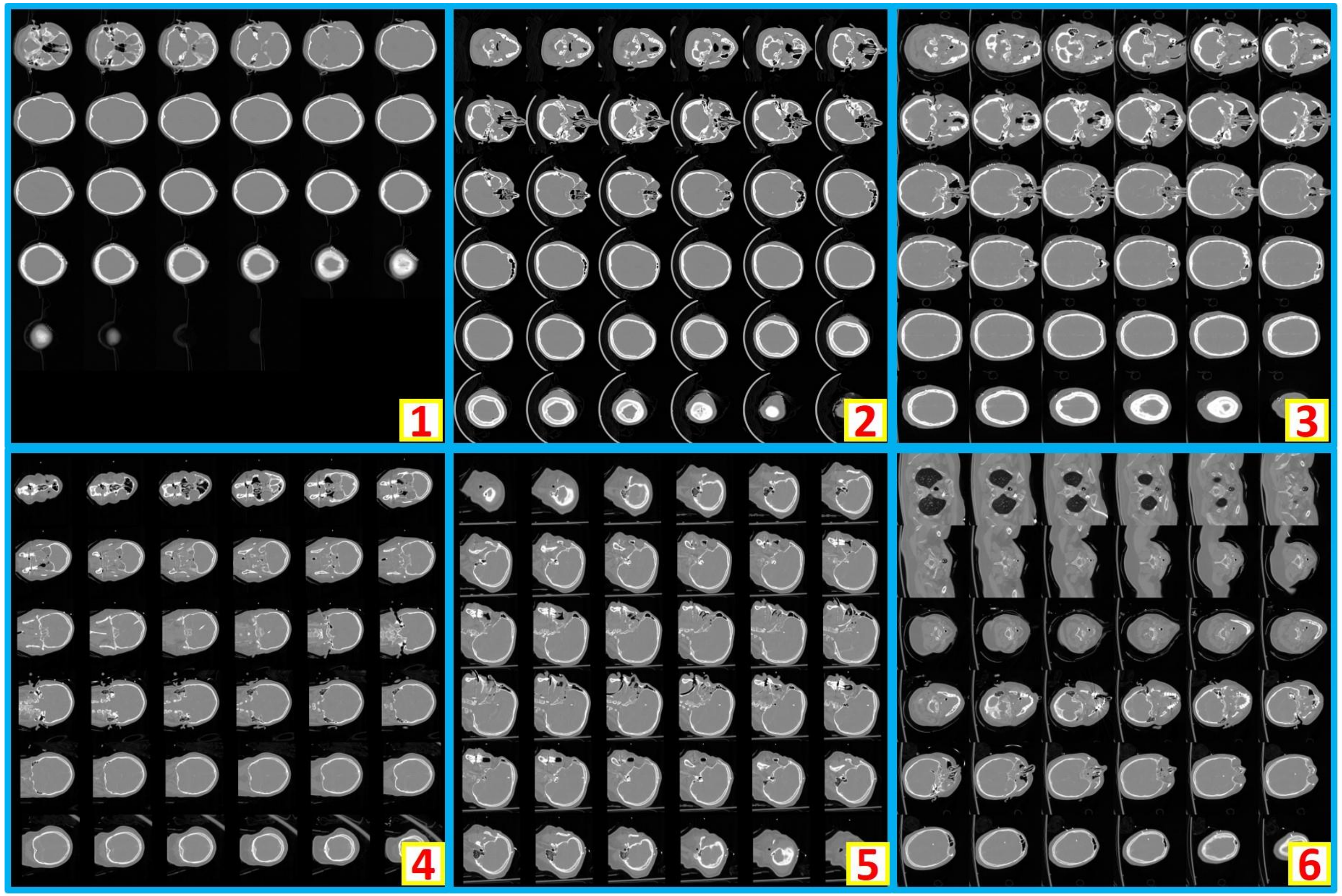
Montage based 3D Medical Image Retrieval from Traumatic Brain Injury Cohort using Deep Convolutional Neural Network

Cailey I. Kerley [1], Yuankai Huo [1*], Shikha Chaganti [2], Shunxing Bao [2], Mayur B. Patel [3], Bennett A. Landman [1,2,4,5]

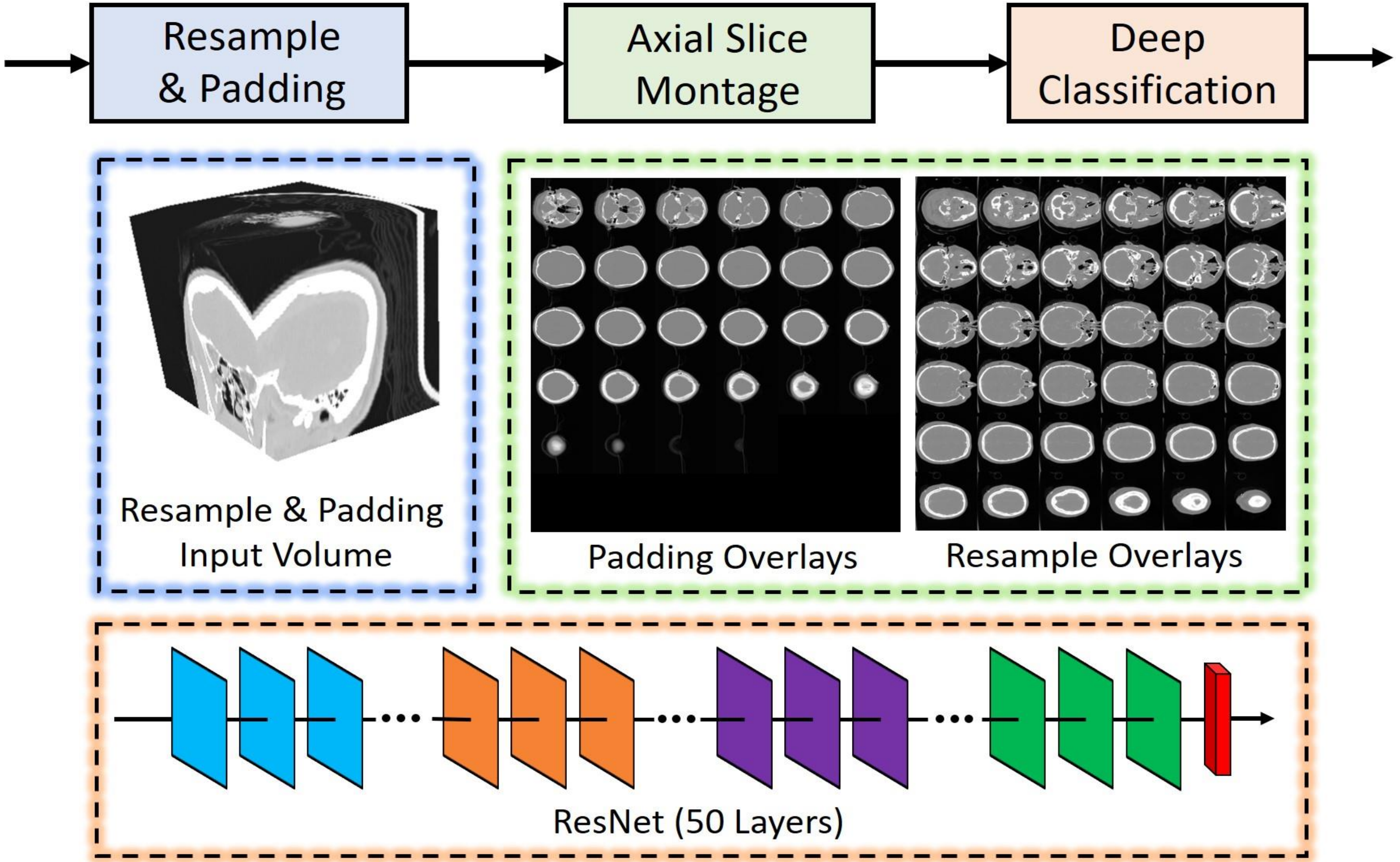
Concept-based Image Retrieval



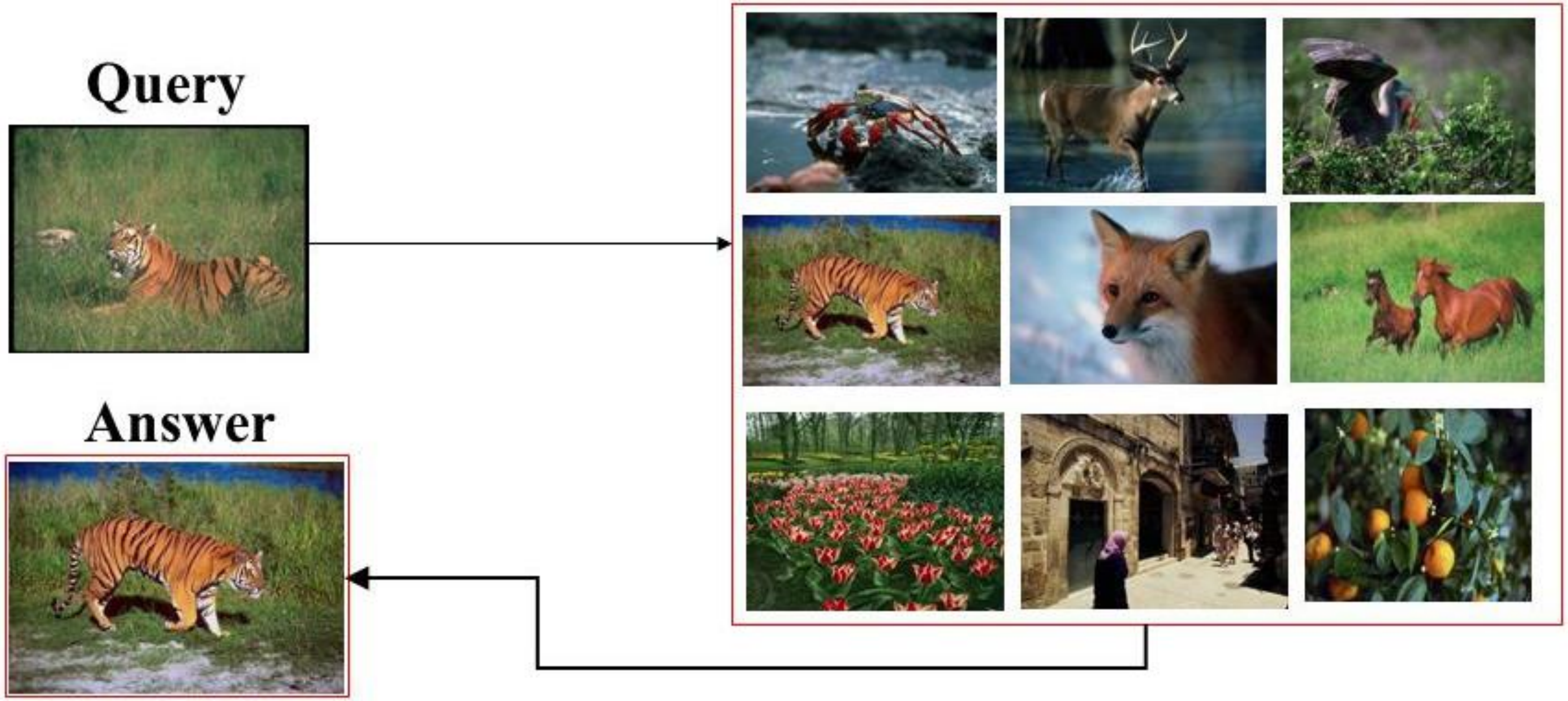
Concept-based Image Retrieval



Concept-based Image Retrieval

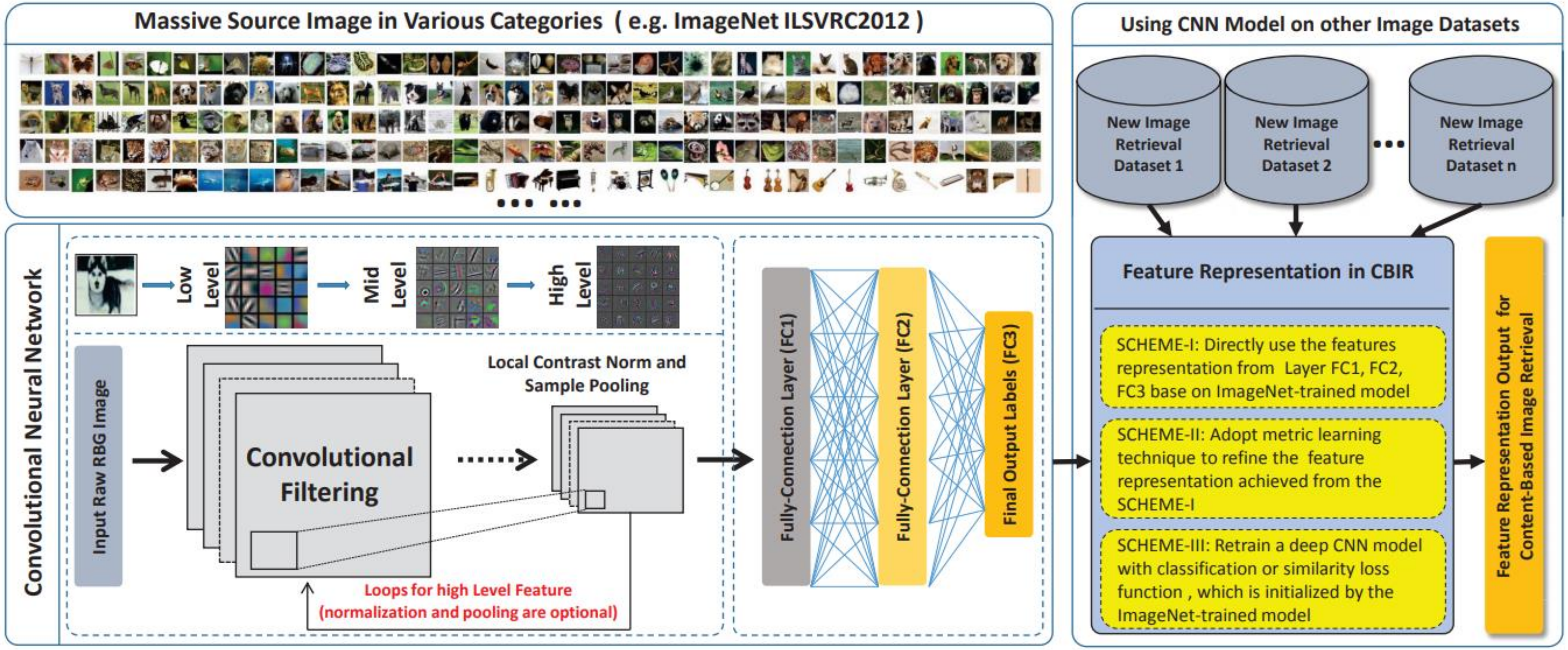


Content-based Image Retrieval



https://www.analyticsvidhya.com/blog/2017/11/information-retrieval-using-kdtree/

Content-based Image Retrieval



(a) Training deep CNN models in an existing domain (ImageNet) (b) Adopting trained model for CBIR in a new domain

https://ink.library.smu.edu.sg/cgi/viewcontent.cgi?referer=&httpsredir=1&article=3320&context=sis_research

Content-based Image Retrieval

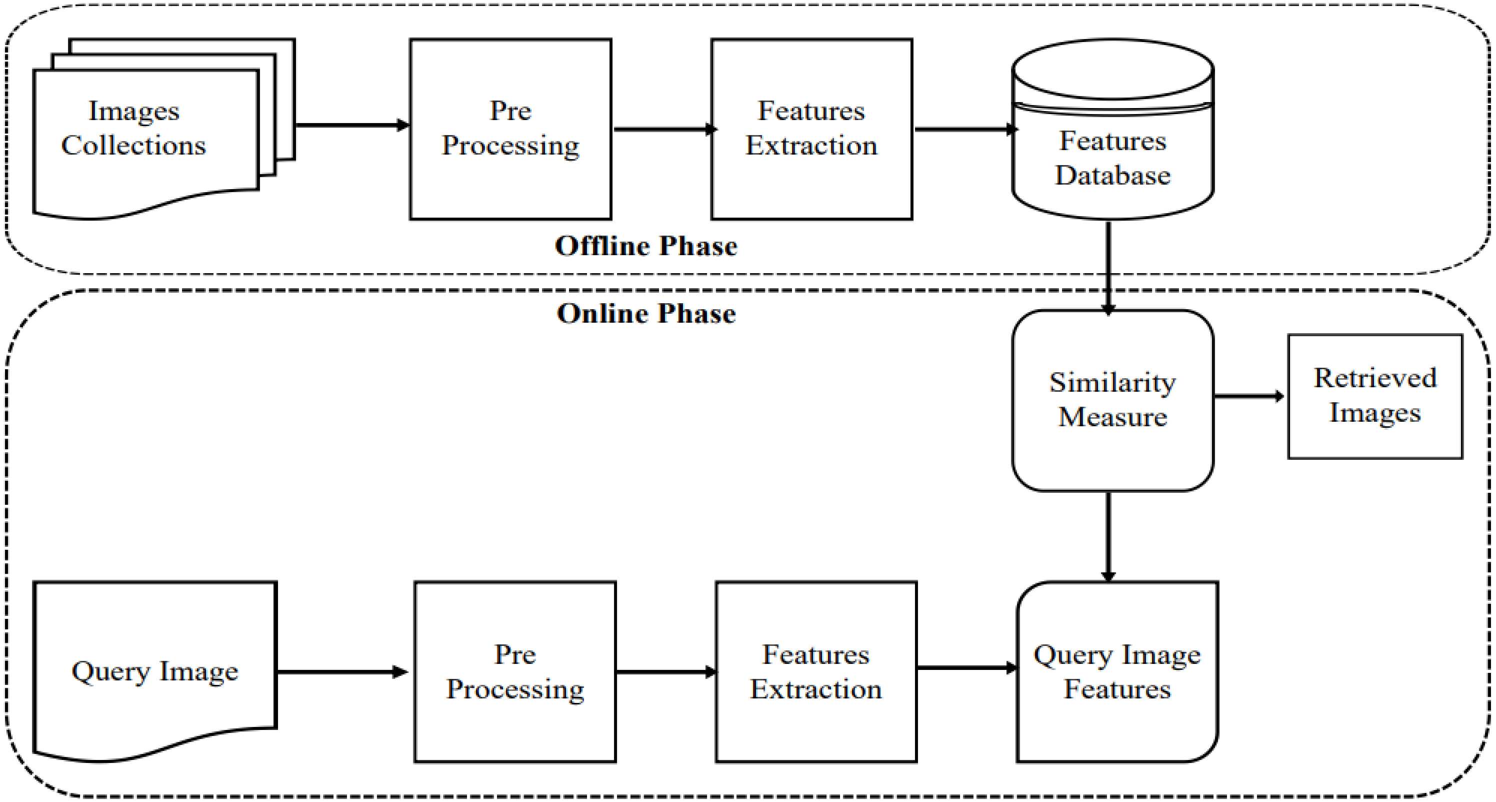


Fig. 1. Block diagram of a generic CBIR system.

https://arxiv.org/ftp/arxiv/papers/1703/1703.08472.pdf

Content-based Image Retrieval

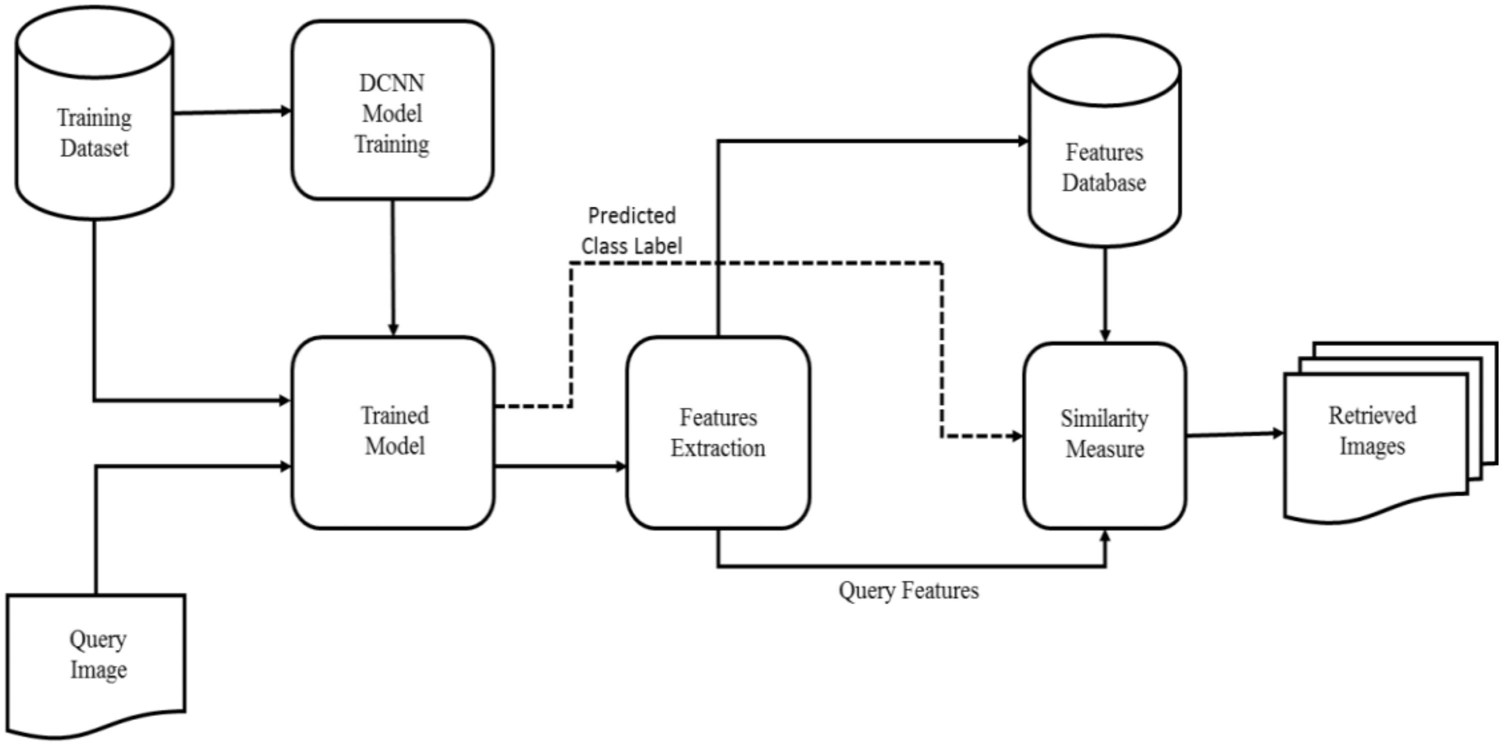


Fig. 2. The proposed framework for content based medical image retrieval using deep convolutional neural network

https://arxiv.org/ftp/arxiv/papers/1703/1703.08472.pdf

Content-based Image Retrieval

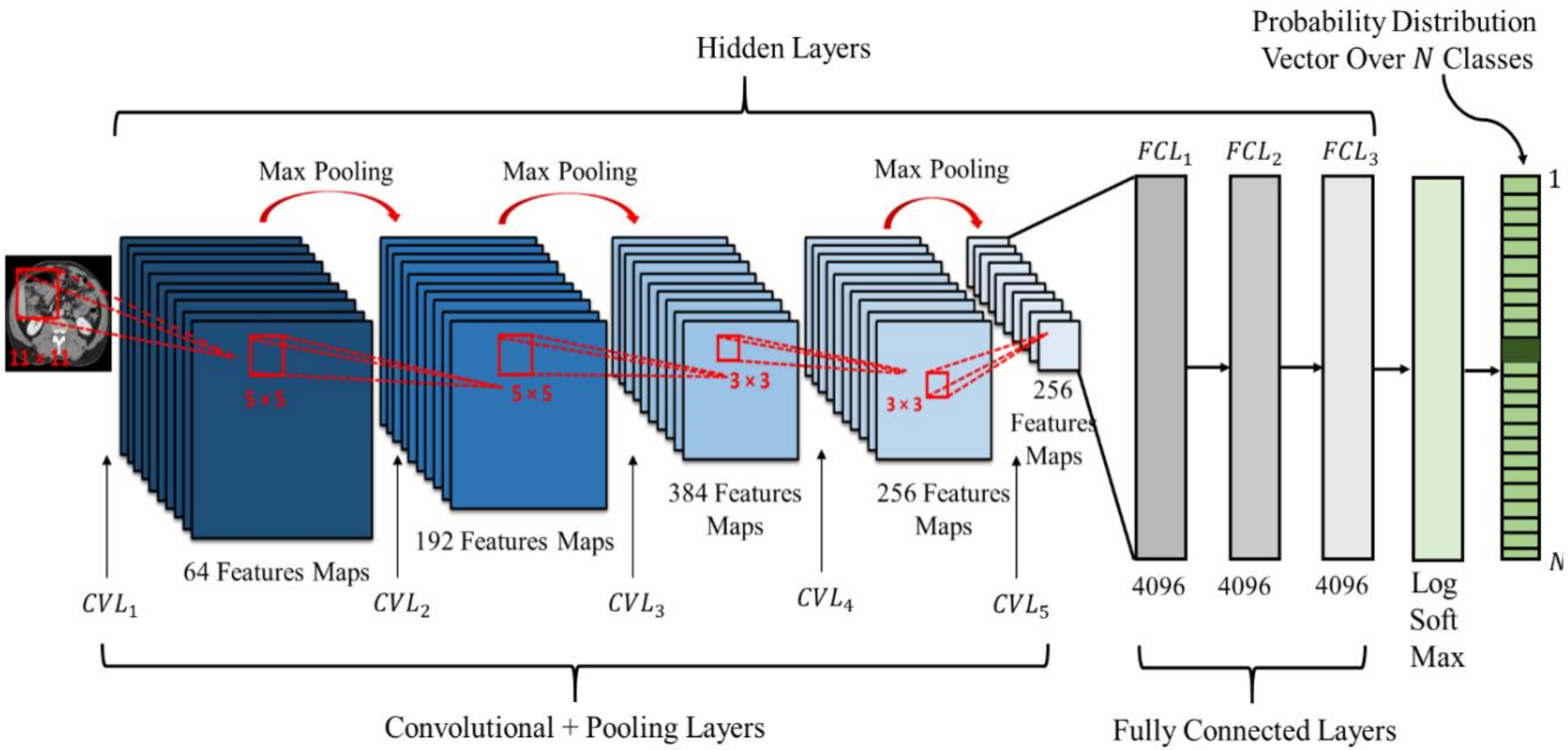
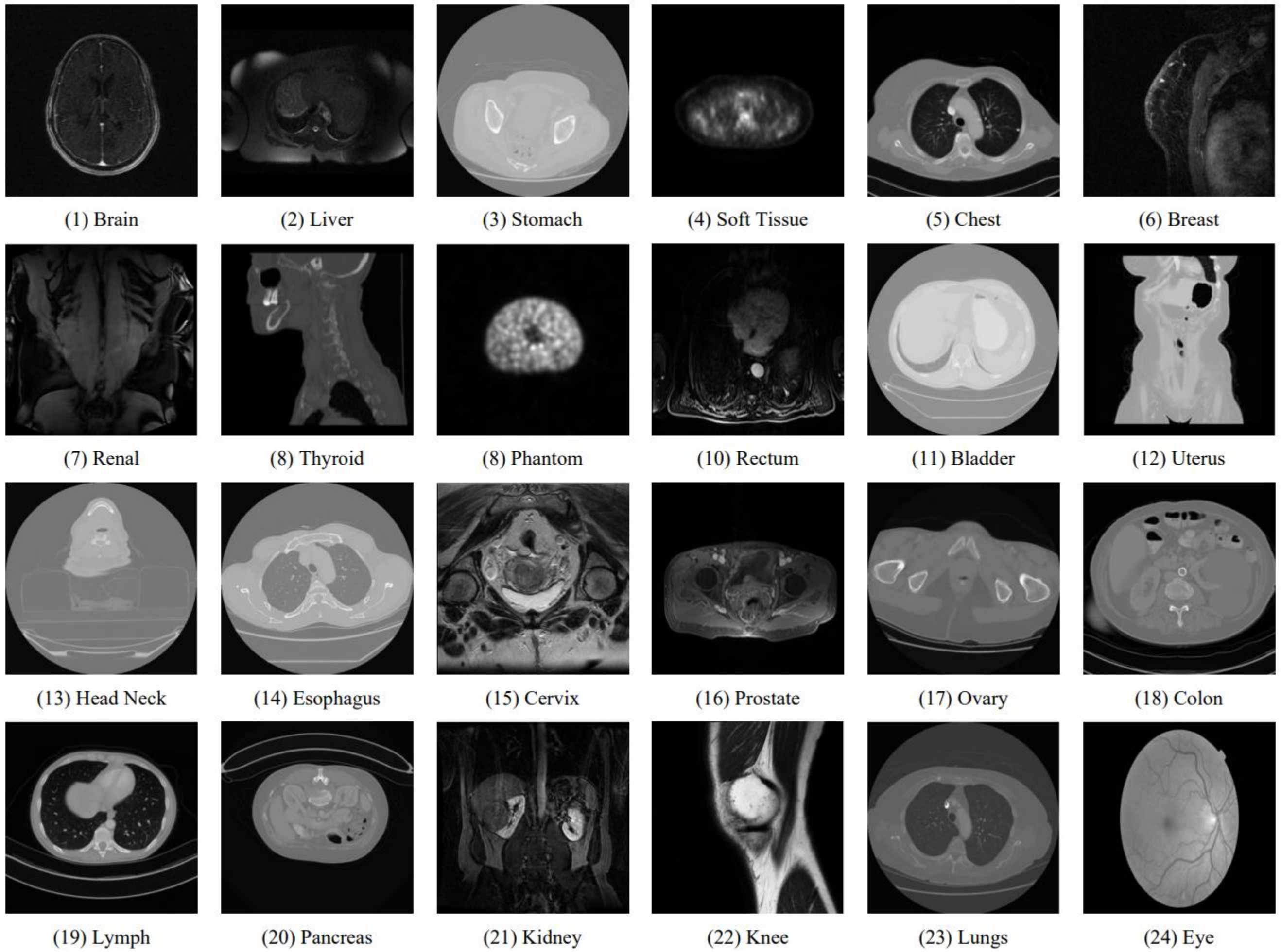


Fig. 3. The DCNN architecture used for the CBMIR task.

https://arxiv.org/ftp/arxiv/papers/1703/1703.08472.pdf

Content-based Image Retrieval



https://arxiv.org/ftp/arxiv/papers/1703/1703.08472.pdf

Content-based Image Retrieval

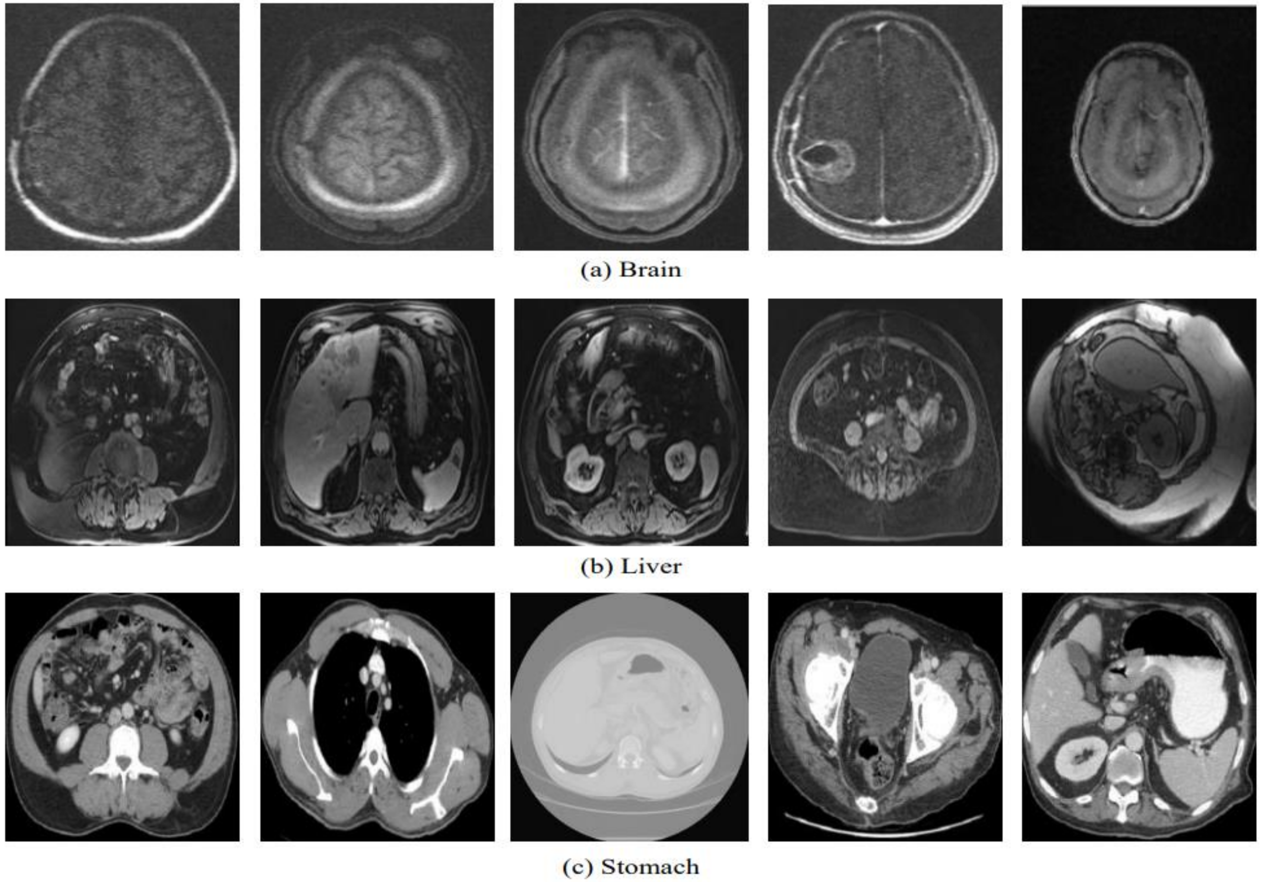


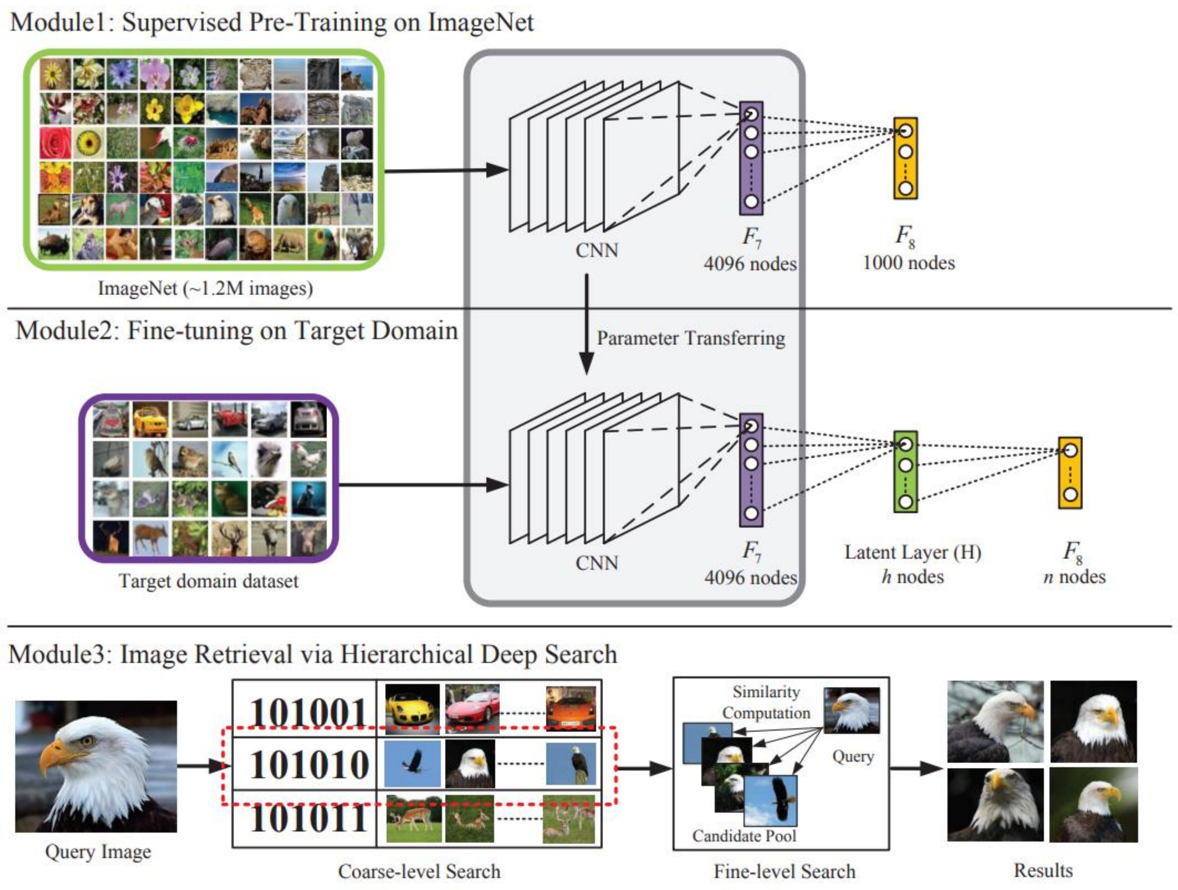
Fig. 6. Example images from different classes showing intra-class variations (a) Brain, (b) Liver and (c) Stomach

https://arxiv.org/ftp/arxiv/papers/1703/1703.08472.pdf

Sketch based retrieval

https://www.youtube.com/watch?v=CafkvyxE4oY

Hash Codes for Fast Image Retrieval



https://www.iis.sinica.edu.tw/~kevinlin311.tw/cvprw15.pdf

Active Learning

Suggestive Annotation: A Deep Active Learning Framework for Biomedical Image Segmentation

Lin Yang[1], Yizhe Zhang[1], Jianxu Chen[1], Siyuan Zhang[2], Danny Z. Chen[1]

[1] Department of Computer Science and Engineering,
University of Notre Dame, Notre Dame, IN 46556, USA
[2] Department of Biological Sciences, Harper Cancer Research Institute,
University of Notre Dame, Notre Dame, IN 46556, USA

Active Learning

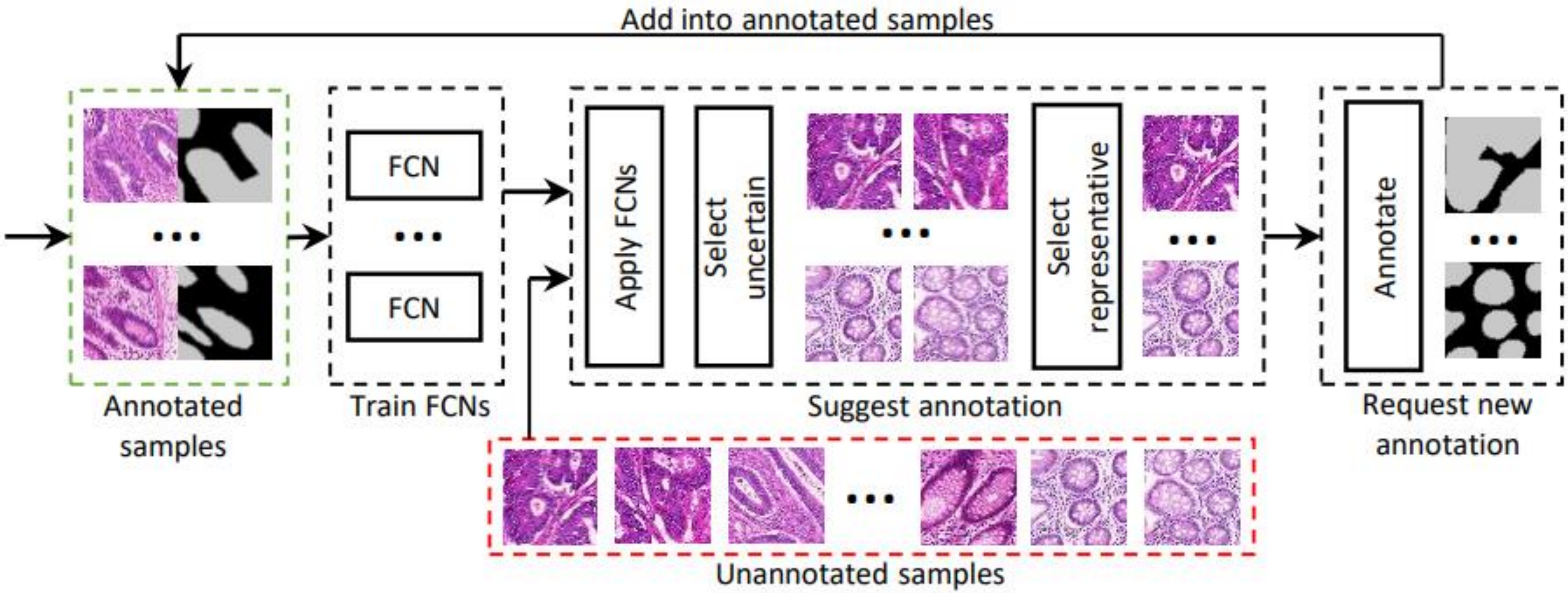


Fig. 1. Illustrating our overall deep active learning framework.

Active Learning

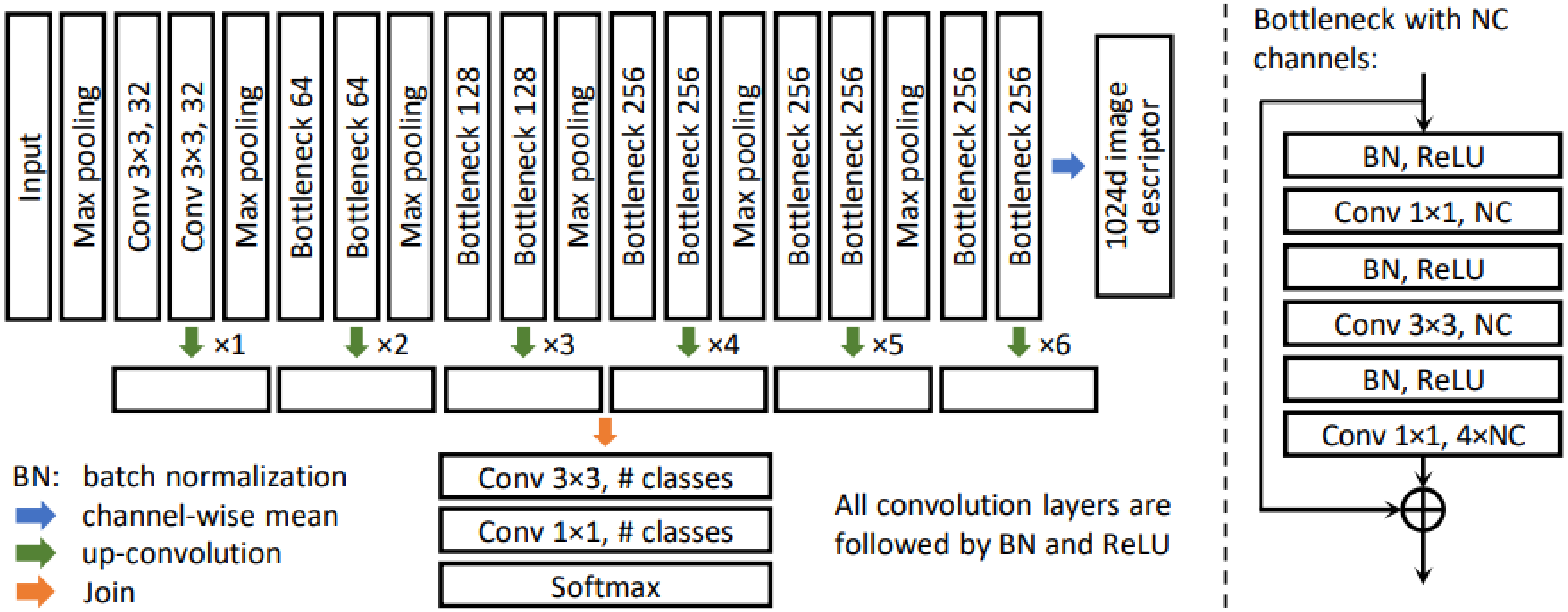
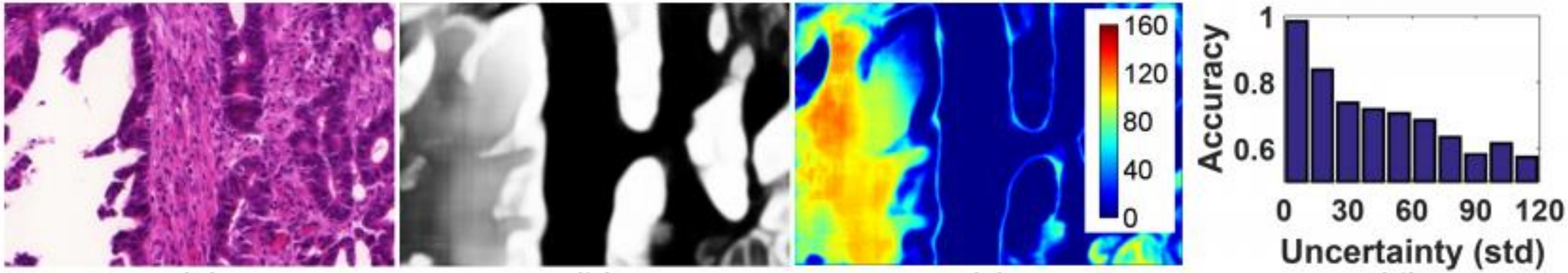


Fig. 2. Illustrating the detailed structure of our FCN components.

Active Learning



(a) (b) (c) (d)

Fig. 3. (a) An original image; (b) the probability map produced by our FCNs for (a); (c) uncertainty estimation of the result; (d) relation between uncertainty estimation and pixel accuracy on the testing data. This shows that the test accuracy is highly correlated with our uncertainty estimation.

Active Learning

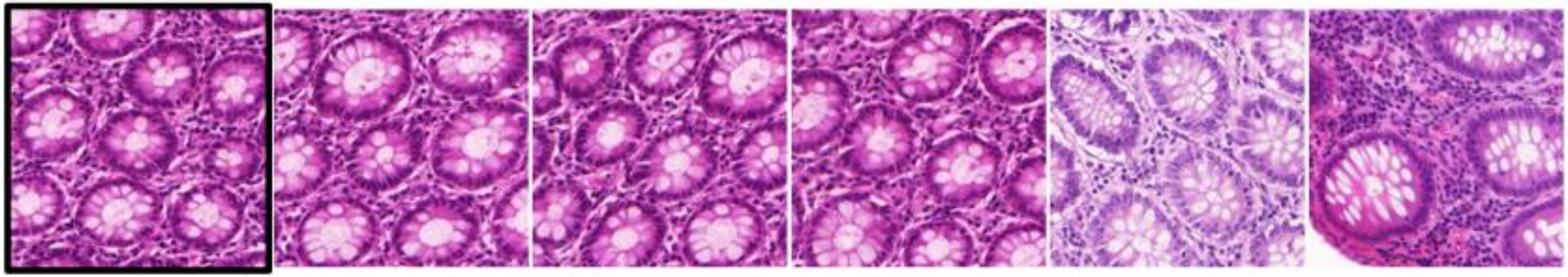


Fig. 4. Illustrating similarity estimation: The 5 images on the right have the highest similarity scores with respect to the leftmost images among all training images in [14].

Active Learning

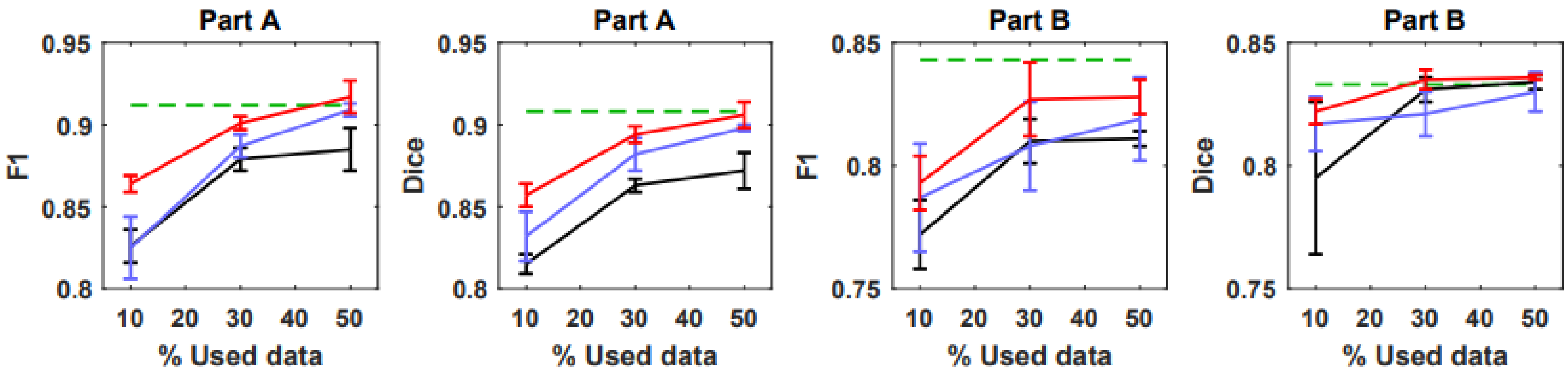
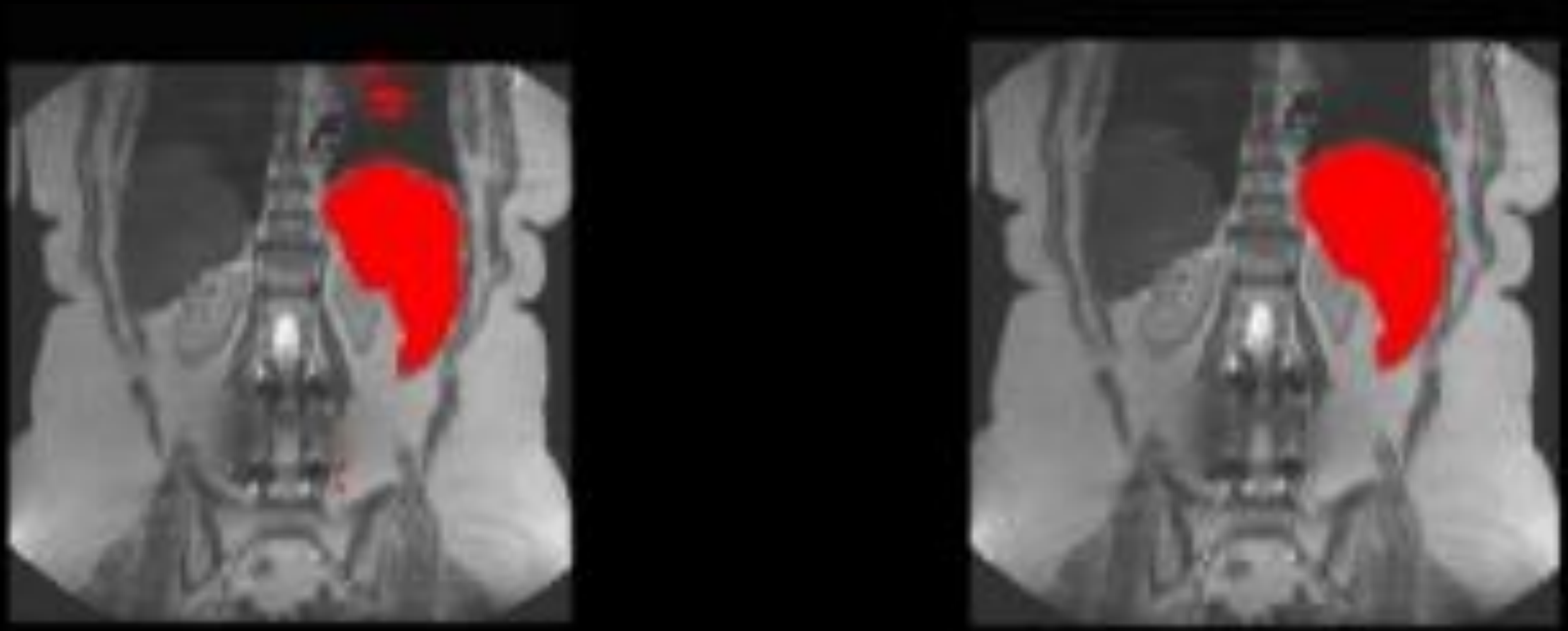


Fig. 5. Comparison using limited training data for gland segmentation: The black curves are for the results of random query, the blue curves are for the results of uncertainty query, the red curves are for the results by our annotation suggestion, and the dashed green lines are for the current state-of-the-art results using full training data.

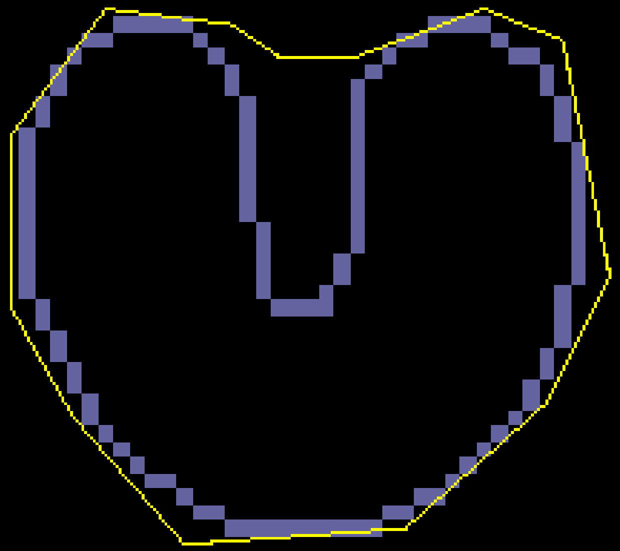
Post-processing

- Active Shape Model,
- Level Set,
- Graph Cut,
- MRF/CRF,
- Corrective Learning

Post Processing



Active Shape Model



http://medpure.blogspot.com/2012/03/active-contour-in-c.html

Deep Learning + ASM

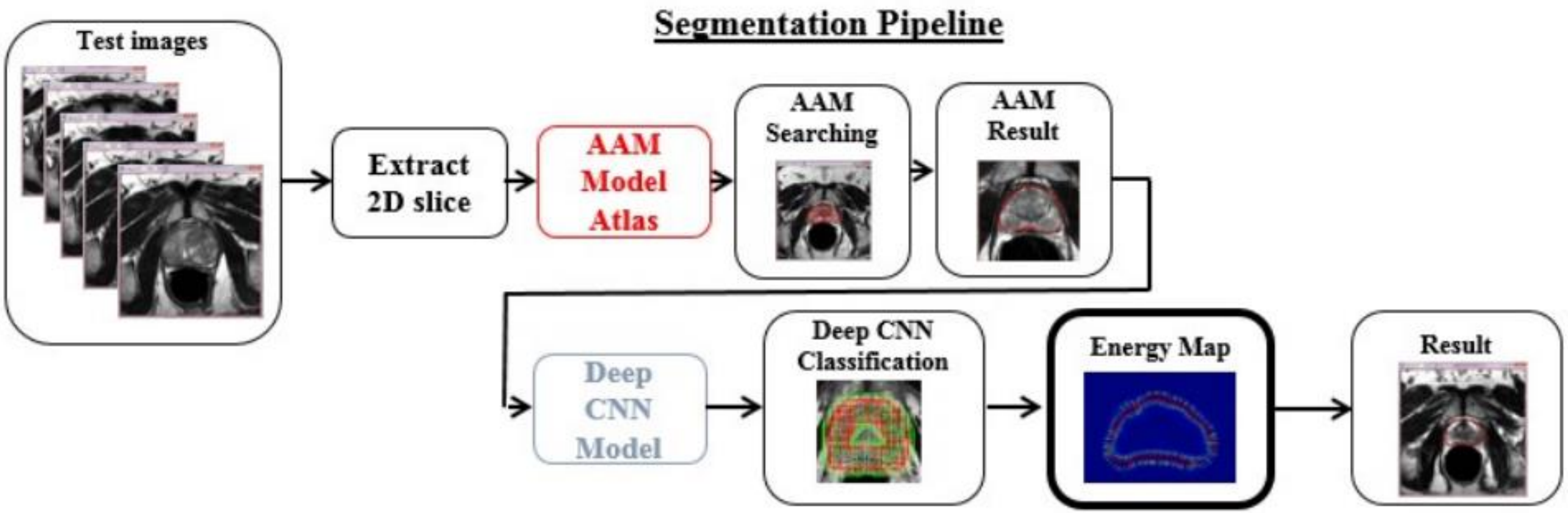
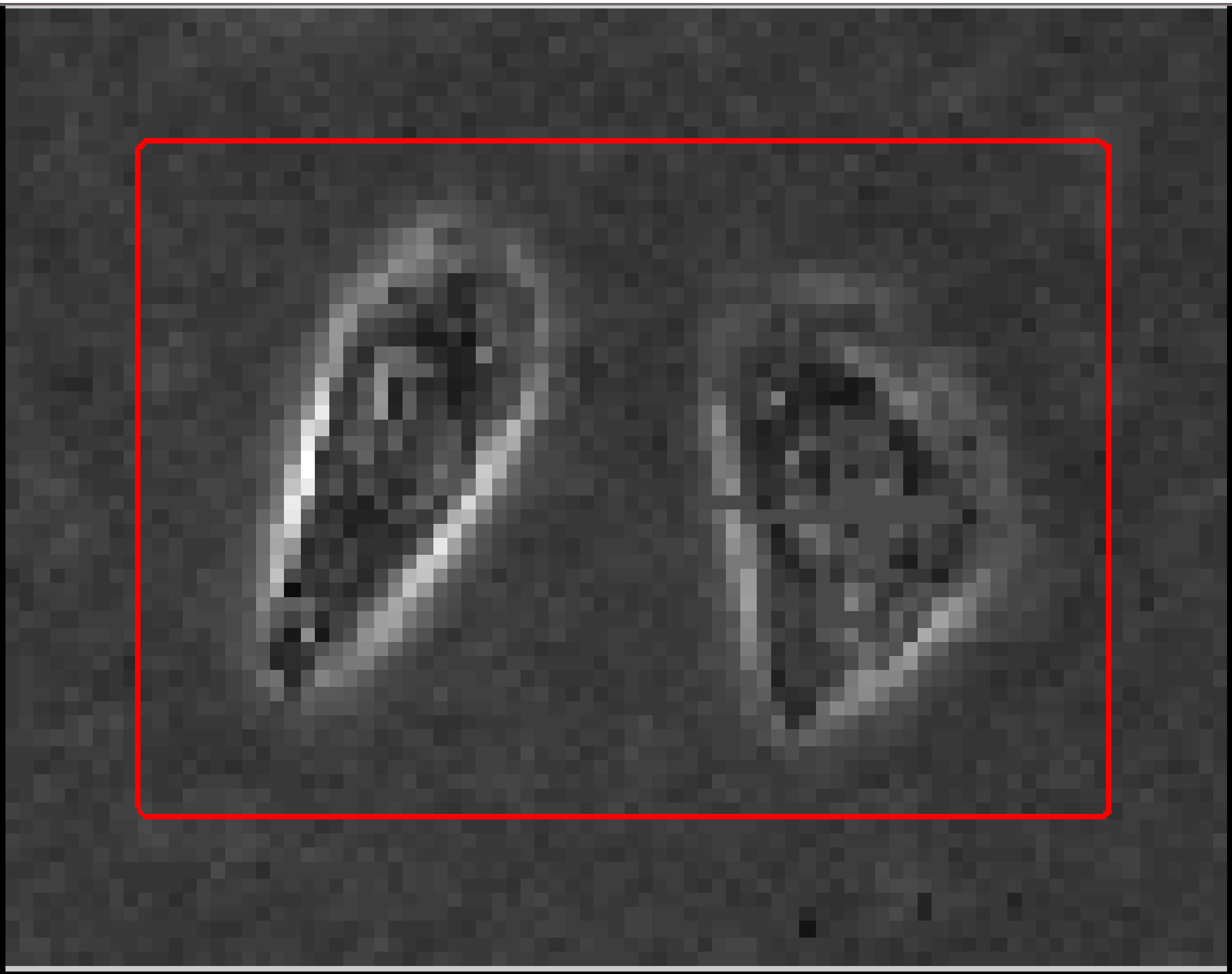


Figure 1. Proposed Model Schema

file:///C:/Users/huoyu/Downloads/97842l.pdf

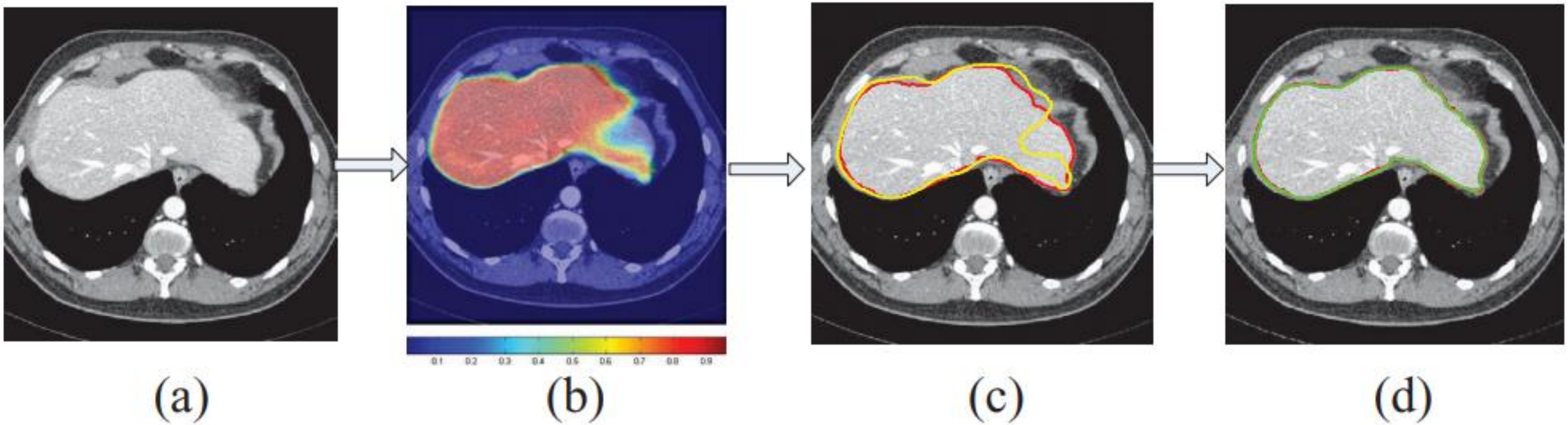
Level Set



https://www.mathworks.com/matlabcentral/fileexchange/12711-level-set-for-image-segmentation

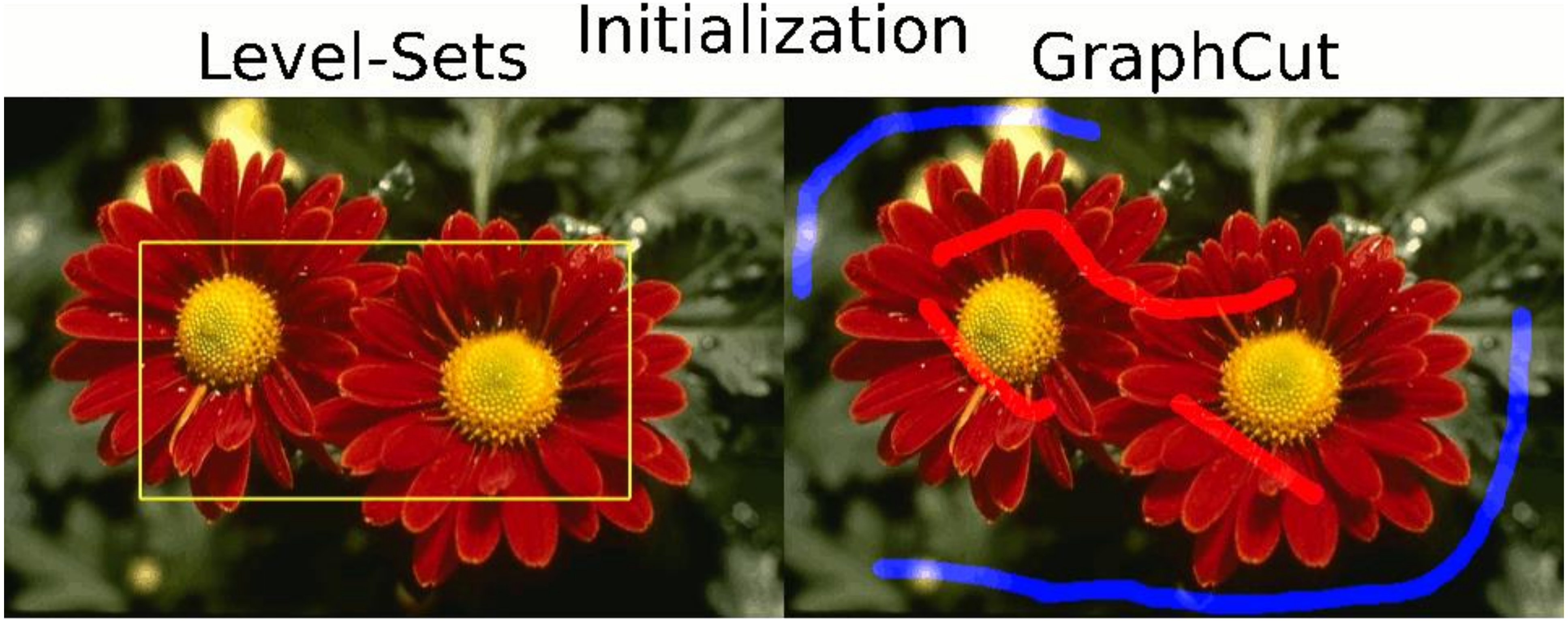
http://blog.sciencenet.cn/home.php?mod=space&uid=467350&do=blog&id=361285

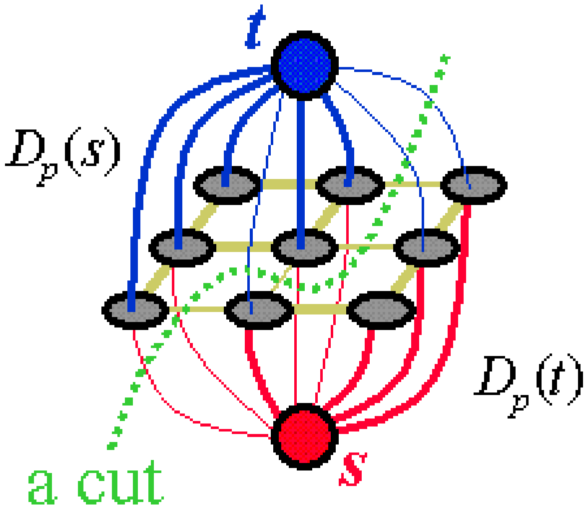
Deep + Levelset



http://iopscience.iop.org/article/10.1088/1361-6560/61/24/8676/pdf

Graph-Cut





http://www.csd.uwo.ca/courses/CS4487a/HW3/hw3.html

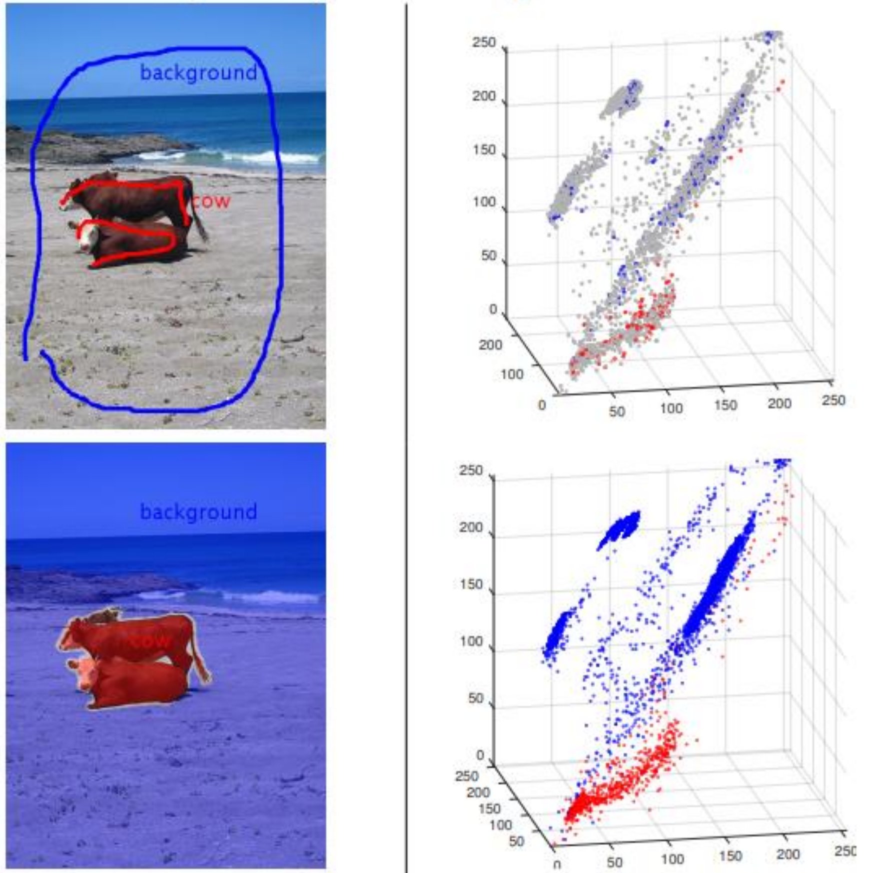
https://www.google.com/url?sa=i&source=images&cd=&ved=2ahUKEwjkoairz6zeAhWNT98KHXiHBzoQjxx6BAgBEAI&url=https%3A%2F%2Fwww.datasciencecentral.com%2Fprofiles%2Fblogs%2Finteractive-image-segmentation-with-graph-cut-in-python&psig=AOvVaw2e1ToesEdlofxm5Xrzq88K&ust=1540935725336468

Deep learning + graph cut

Normalized Cut Loss for Weakly-supervised CNN Segmentation

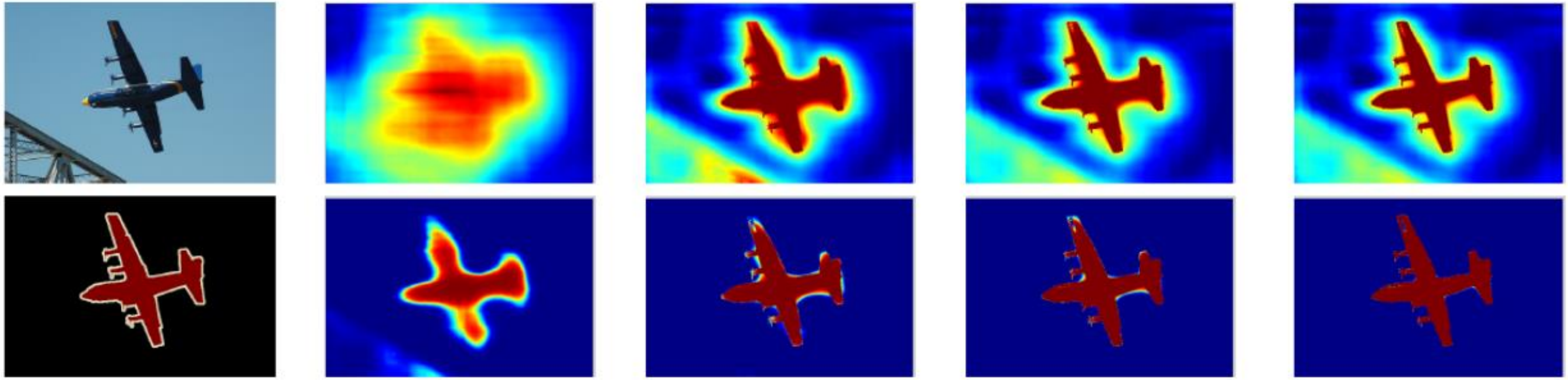
Meng Tang[2,1*] Abdelaziz Djelouah[1] Federico Perazzi[1]
Yuri Boykov[2] Christopher Schroers[1]
[1]Disney Research, Zürich, Switzerland
[2]Computer Science, University of Waterloo, Canada

partially labeled input data



(a) image segmentation | (b) clustering (e.g. RGB)

Conditional Random Fields



Image/G.T. DCNN output CRF Iteration 1 CRF Iteration 2 CRF Iteration 10

https://blog.csdn.net/u011974639/article/details/79134409

CRF-RNN

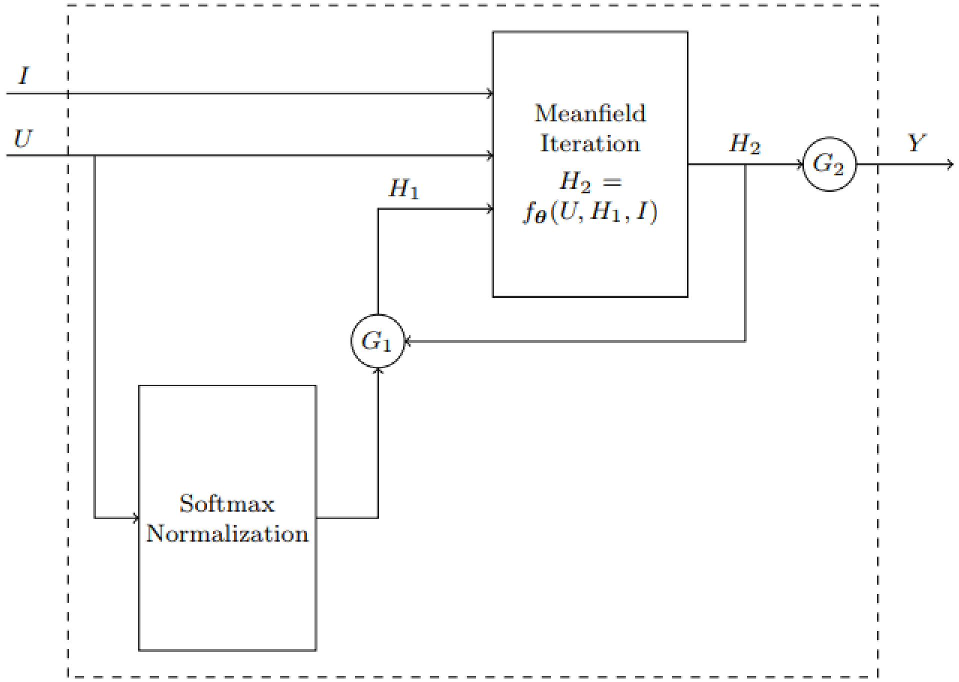


Figure 2. **The CRF-RNN Network.** We formulate the iterative mean-field algorithm as a Recurrent Neural Network (RNN). Gating functions G_1 and G_2 are fixed as described in the text.

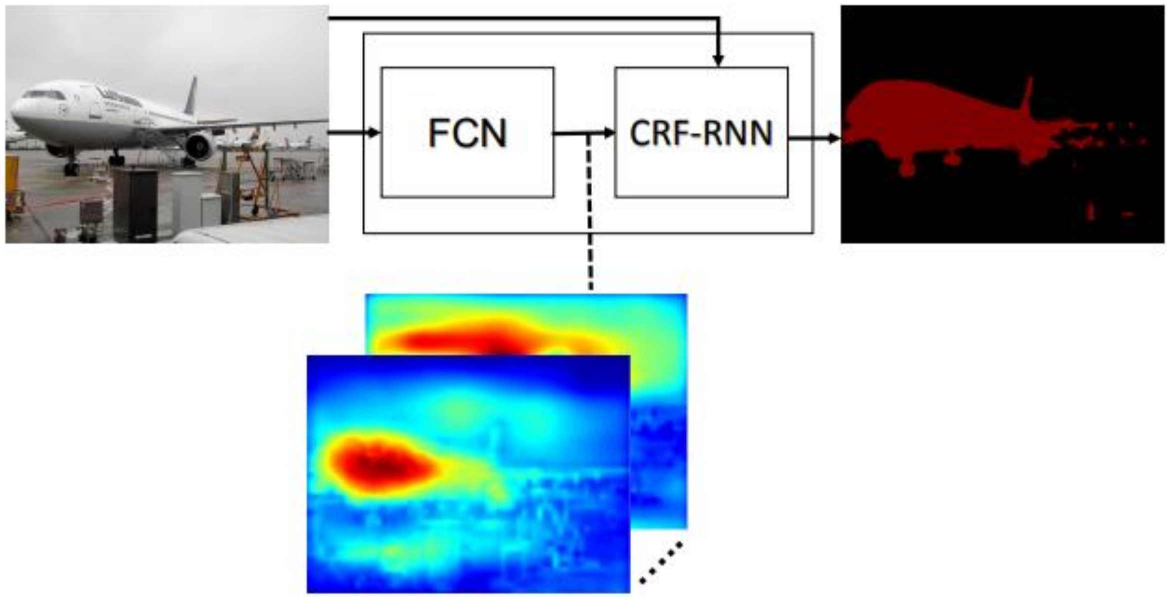


Figure 3. **The End-to-end Trainable Network.** Schematic visualization of our full network which consists of a CNN and the CNN-CRF network. Best viewed in colour.

https://www.robots.ox.ac.uk/~szheng/papers/CRFasRNN.pdf

Corrective Learning

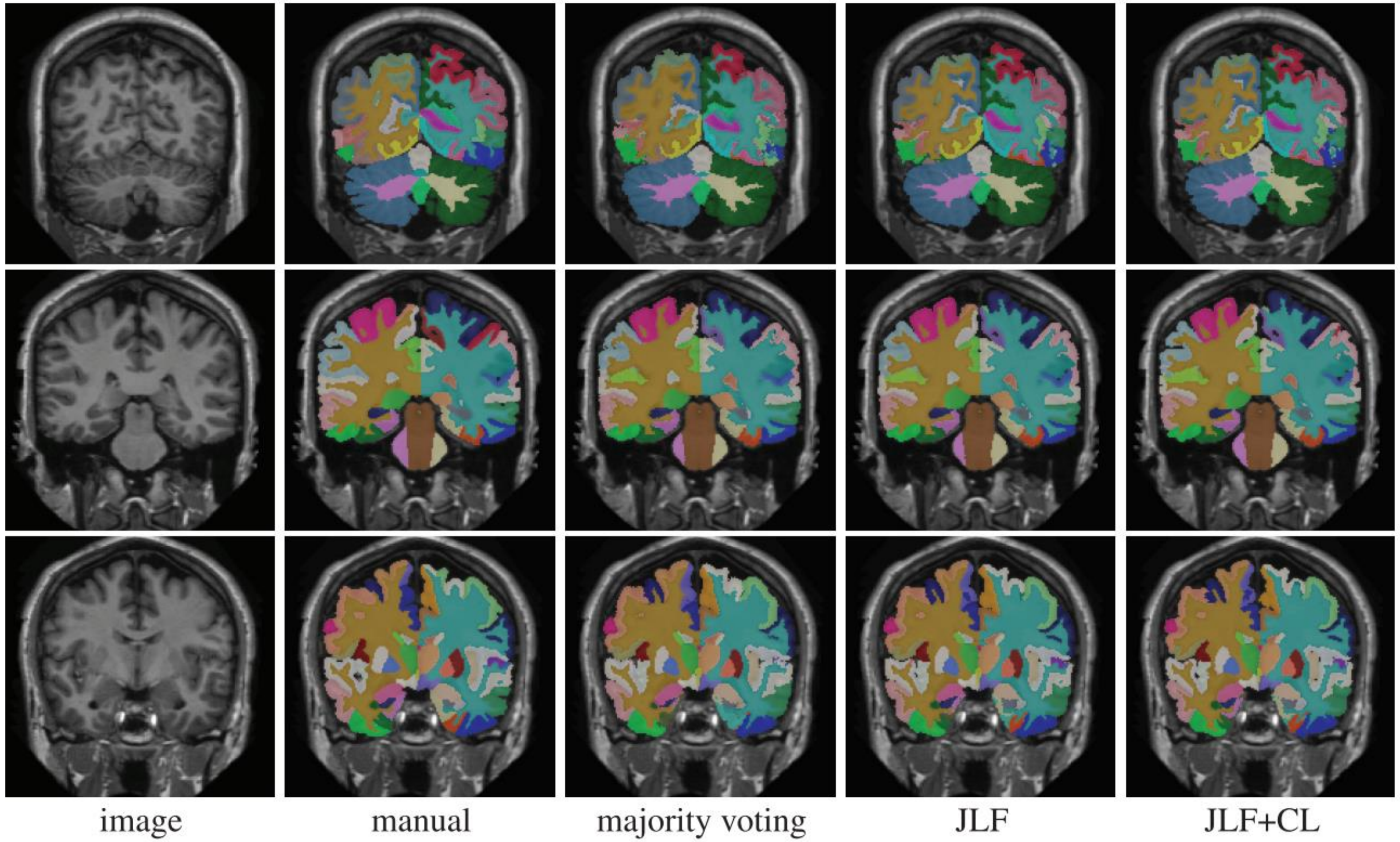
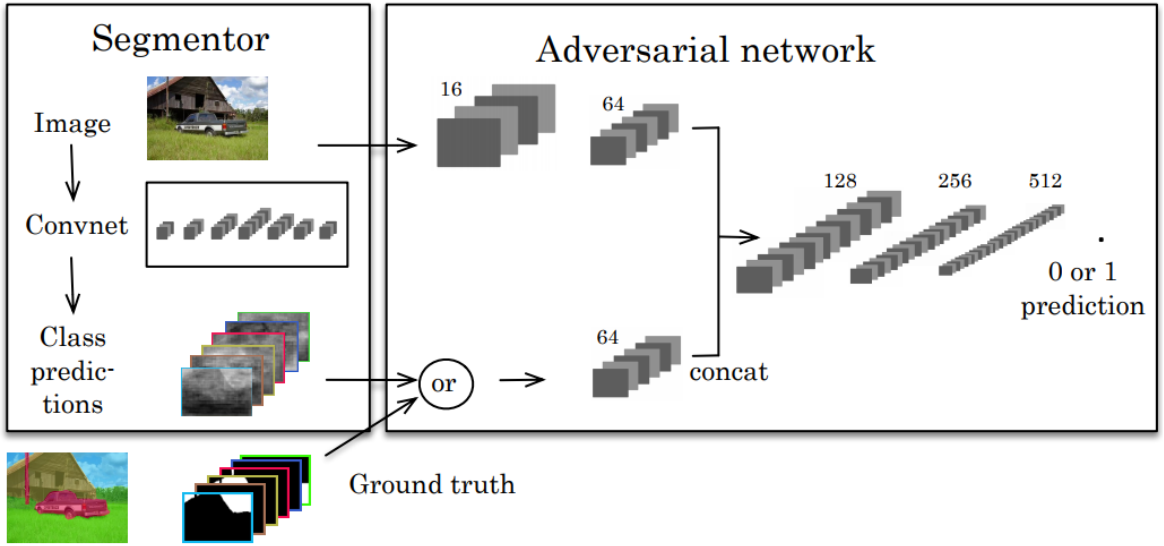
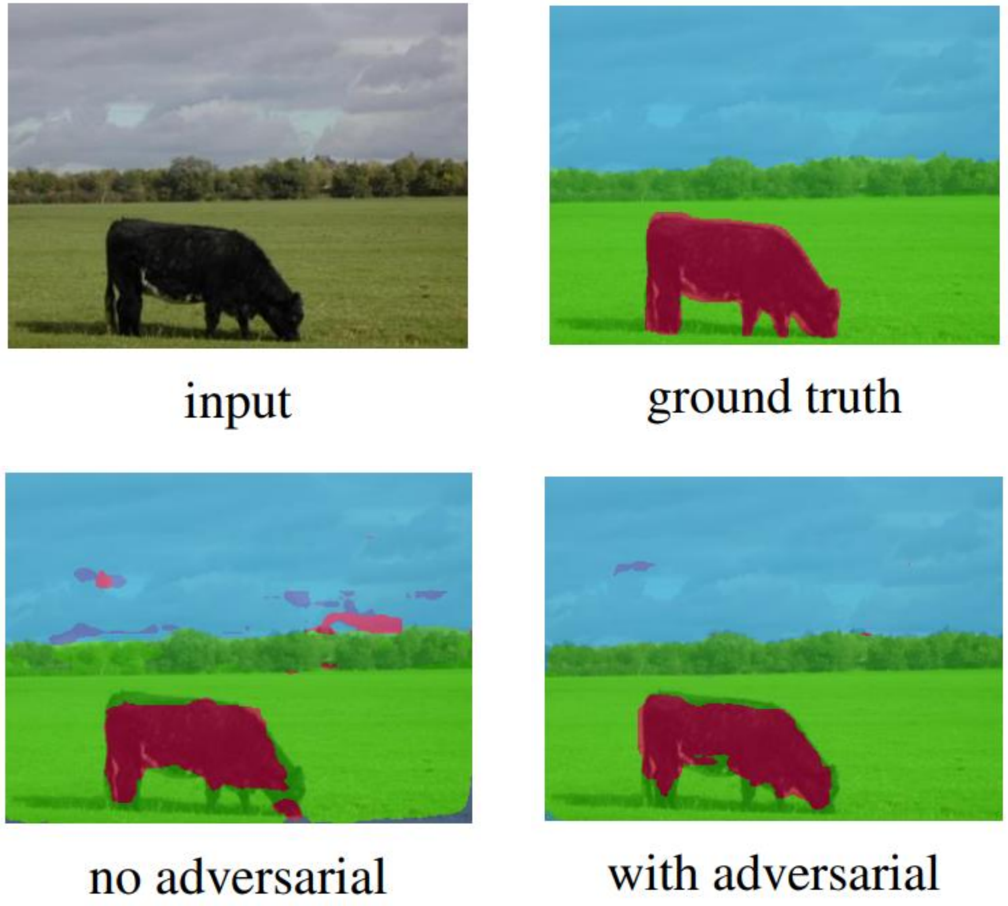


FIGURE 1 | Segmentations produced by manual segmentation, majority voting, joint label fusion (JLF), and joint label fusion combined with corrective learning (JLF+CL).

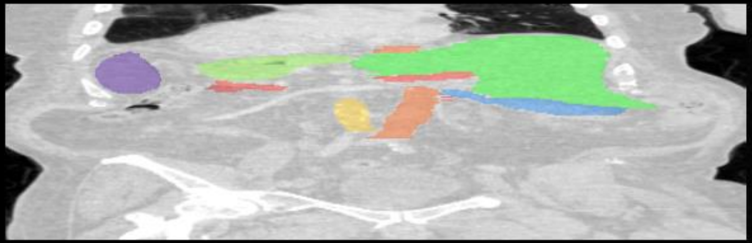
GAN

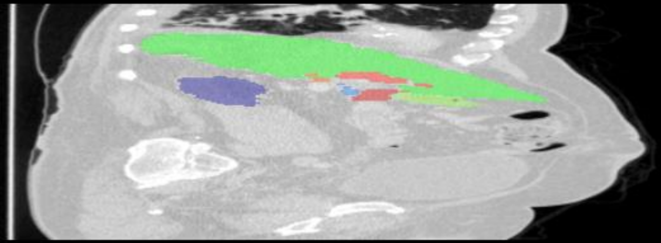
Luc et al, NIPS WS 2016

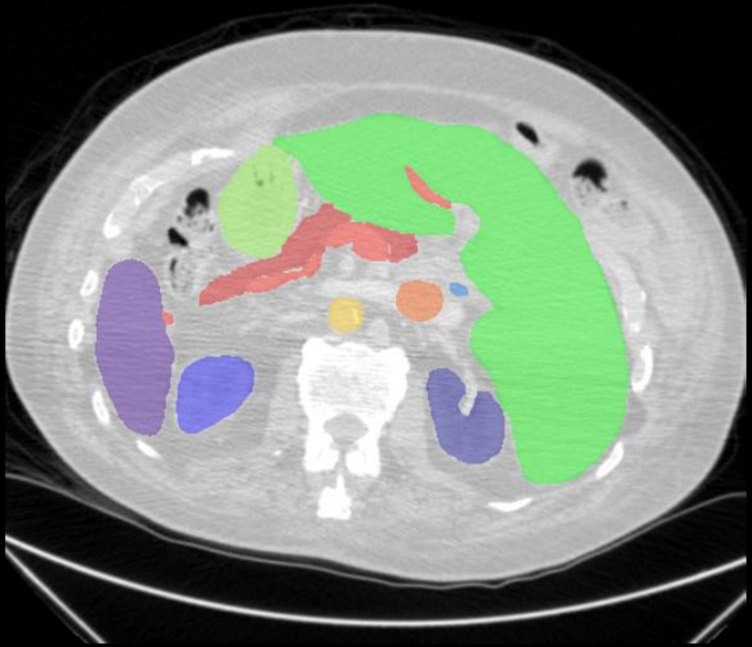




Overlay







Good Papers

A No-Reference Quality Metric for Retinal Vessel Tree Segmentation

Adrian Galdran[1(✉)], Pedro Costa[1], Alessandro Bria[2], Teresa Araújo[1,3], Ana Maria Mendonça[1,3], and Aurélio Campilho[1,3]

[1] INESC-TEC - Institute for Systems and Computer Engineering, Technology and Science, Porto, Portugal
{adrian.galdran,pvcosta,tfaraujo}@inesctec.pt
[2] Università degli studi di Cassino e del Lazio Meridionale, Cassino, Italy
a.bria@unicas.it
[3] Faculdade de Engenharia da Universidade do Porto, Porto, Portugal
{amendon,campilho}@fe.up.pt

Abstract. Due to inevitable differences between the data used for training modern CAD systems and the data encountered when they are deployed in clinical scenarios, the ability to automatically assess the quality of predictions when no expert annotation is available can be critical. In this paper, we propose a new method for quality assessment of retinal vessel tree segmentations in the absence of a reference ground-truth. For this, we artificially degrade expert-annotated vessel map segmentations and then train a CNN to predict the similarity between the degraded images and their corresponding ground-truths. This similarity can be interpreted as a proxy to the quality of a segmentation. The proposed model can produce a visually meaningful quality score, effectively predicting the quality of a vessel tree segmentation in the absence of a manually segmented reference. We further demonstrate the usefulness of our approach by applying it to automatically find a threshold for soft probabilistic segmentations on a per-image basis. For an independent state-of-the-art unsupervised vessel segmentation technique, the thresholds selected by our approach lead to statistically significant improvements in F1-score (+2.67%) and Matthews Correlation Coefficient (+3.11%) over the thresholds derived from ROC analysis on the training set. The score is also shown to correlate strongly with F1 and MCC when a reference is available.

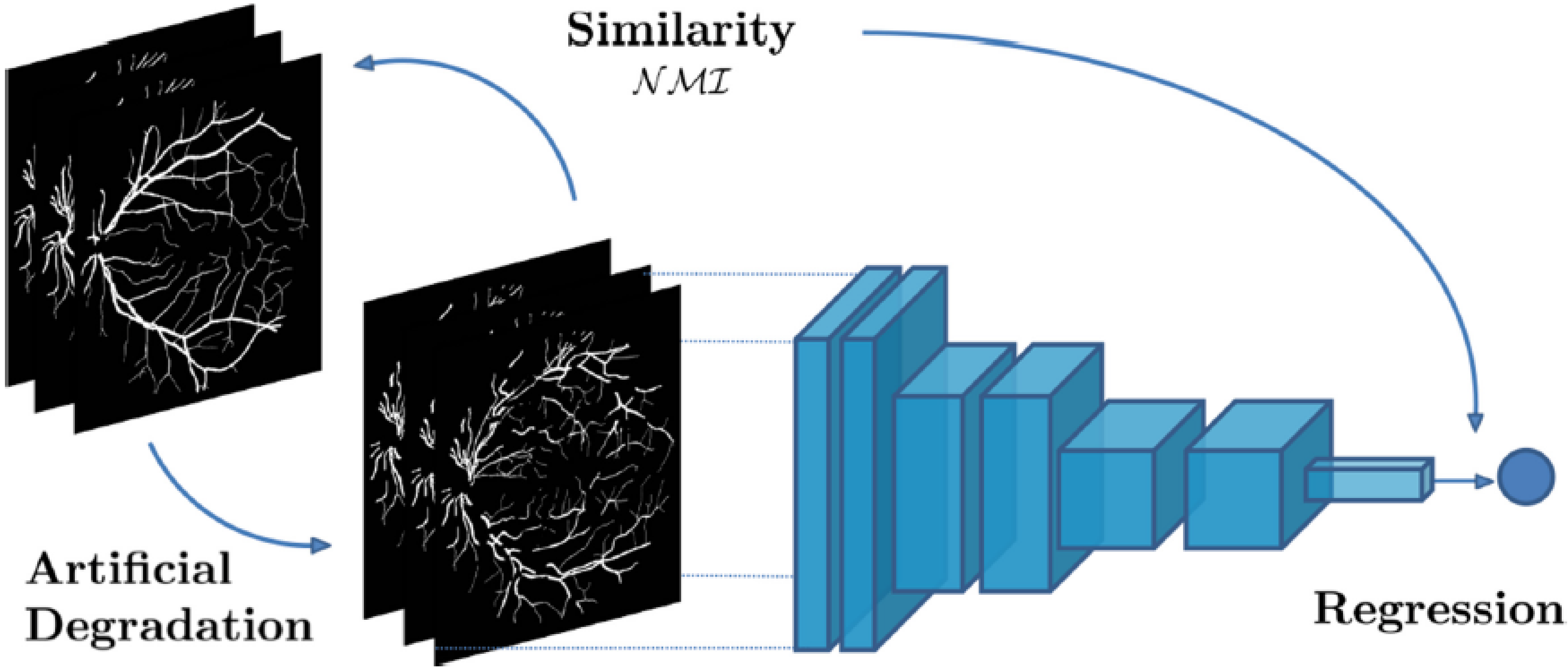


Fig. 1. Representation of the training stage of the proposed method. Similarity between original/degraded vessel maps is measured by Normalized Mutual Information ($\mathcal{NMI}$).

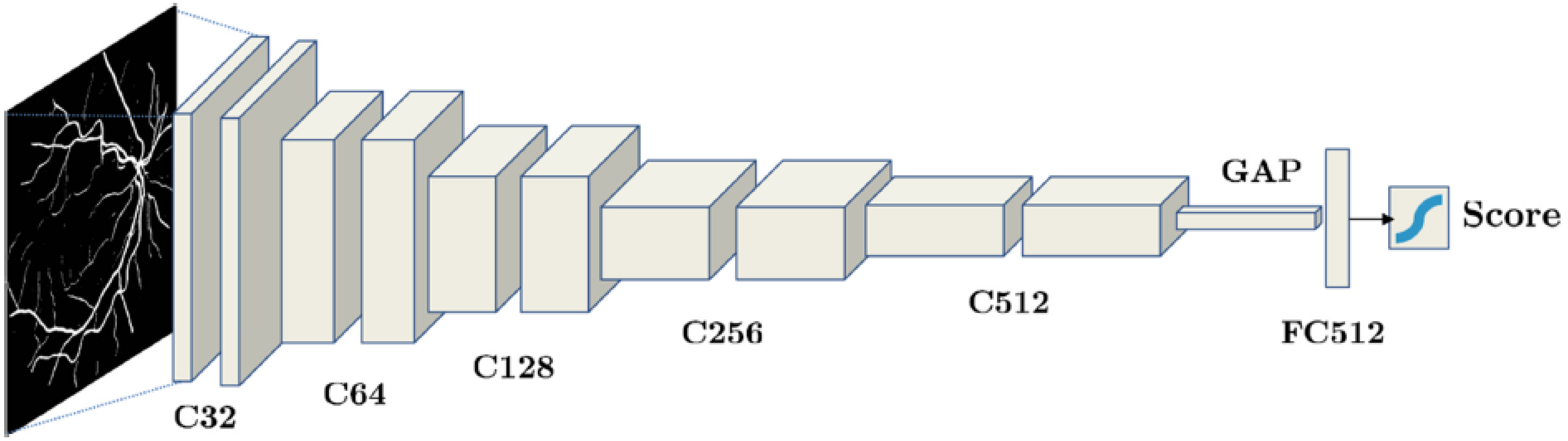


Fig. 3. An architecture for regressing similarity between a degraded vessel tree and a manual segmentation. CN stands for a convolutional layer with N filters of size 3×3.

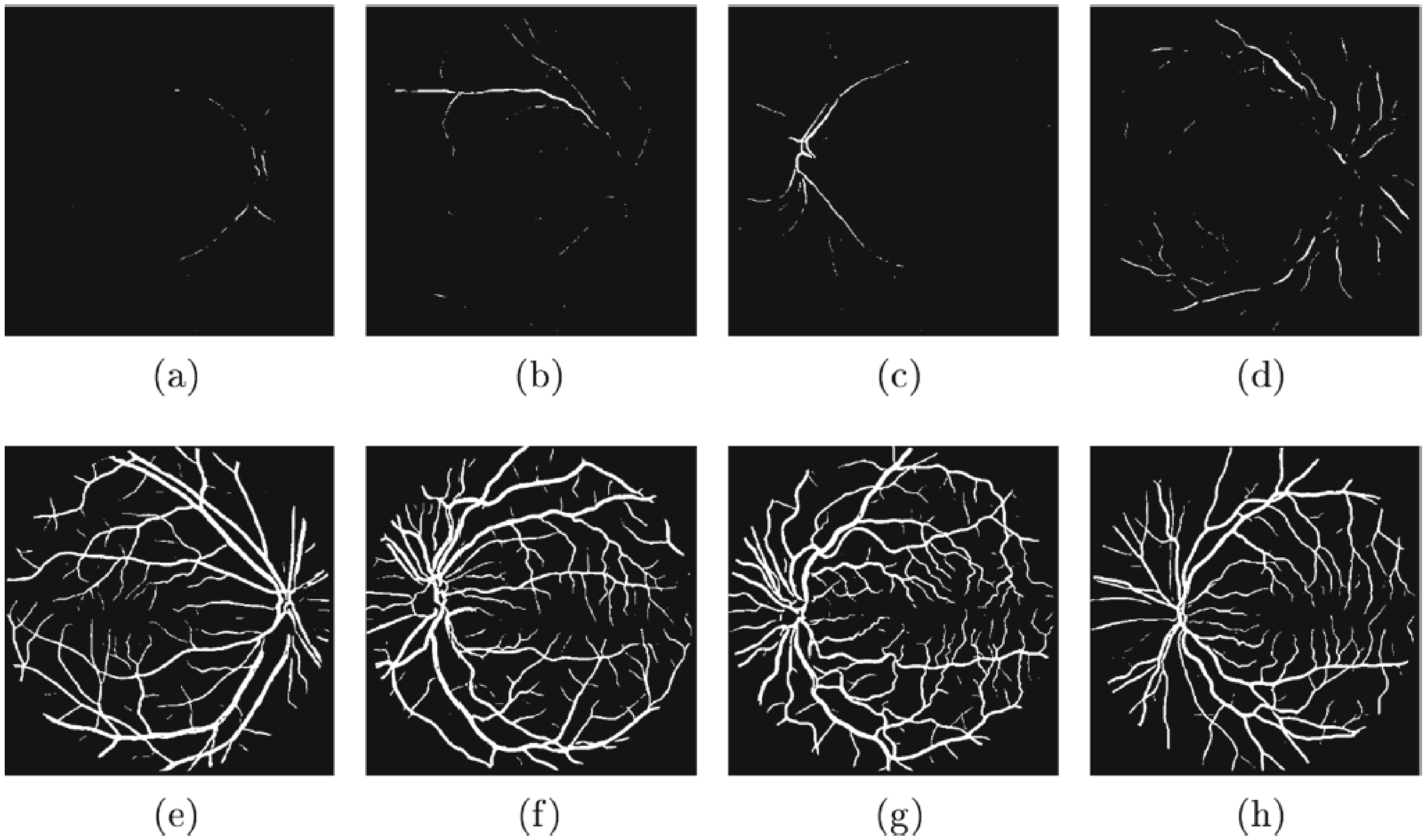


Fig. 4. The four worse and best automatic segmentations extracted from the Messidor dataset with the technique of [9], sorted according to the proposed quality score.

Order-Sensitive Deep Hashing for Multimorbidity Medical Image Retrieval

Zhixiang Chen[1,2,3], Ruojin Cai[1], Jiwen Lu[1,2,3(✉)], Jianjiang Feng[1,2,3], and Jie Zhou[1,2,3]

[1] Department of Automation, Tsinghua University, Beijing, China
lujiwen@tsinghua.edu.cn
State Key Lab of Intelligent Technologies and Systems, Tsinghua University, Beijing, China
[3] Beijing National Research Center for Information Science and Technology, Beijing, China

Abstract. In this paper, we propose an order-sensitive deep hashing for scalable medical image retrieval in the scenario of coexistence of multiple medical conditions. The pairwise similarity preservation in existing hashing methods is not suitable for this multimorbidity medical image retrieval problem. To capture the multilevel semantic similarity, we formulate it as a multi-label hashing learning problem. We design a deep hash model for powerful feature extraction and preserve the ranking list with a triplet based ranking loss for better assessment assistance. We further introduce the cross-entropy based multi-label classification loss to exploit multi-label information. We solve the optimization problem by continuation to reduce the quantization loss. We conduct extensive experiments on a large database constructed on the NIH Chest X-ray database to validate the efficacy of the proposed algorithm. Experimental results demonstrate that our order sensitive deep hashing leads to superior performance compared with several state-of-the-art hashing methods.

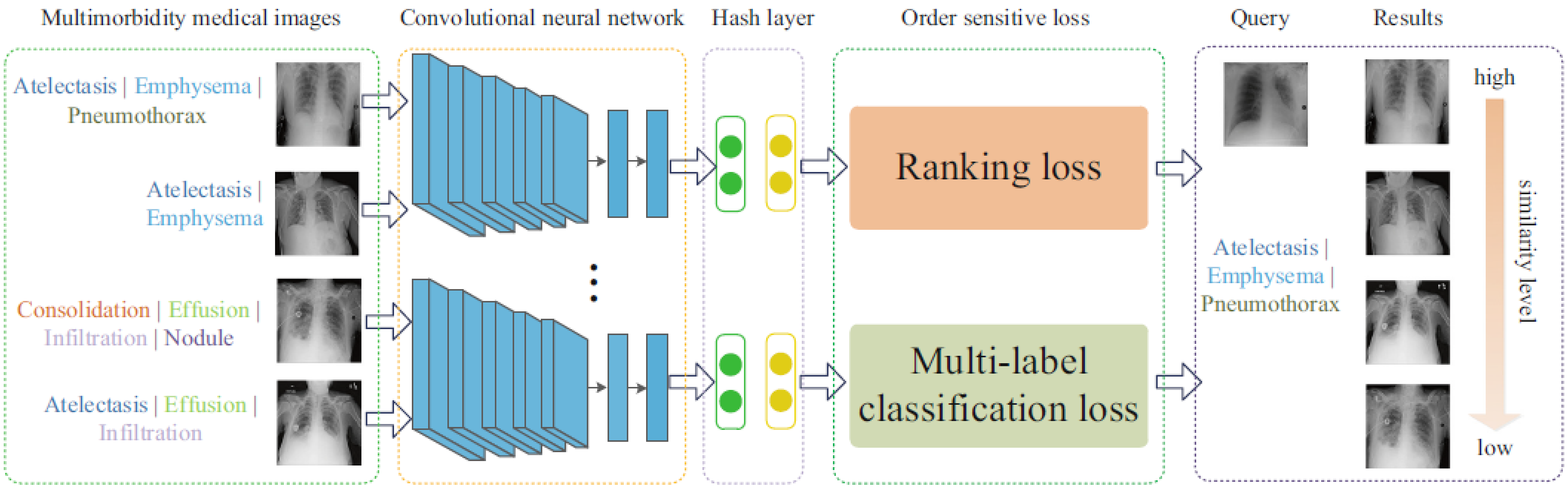


Fig. 1. Overview of the OSDH method. We learn to hash on multimorbidity medical images with order preserving by deep learning model. The retrieval results with learned binary codes are expected to preserve the multilevel similarity

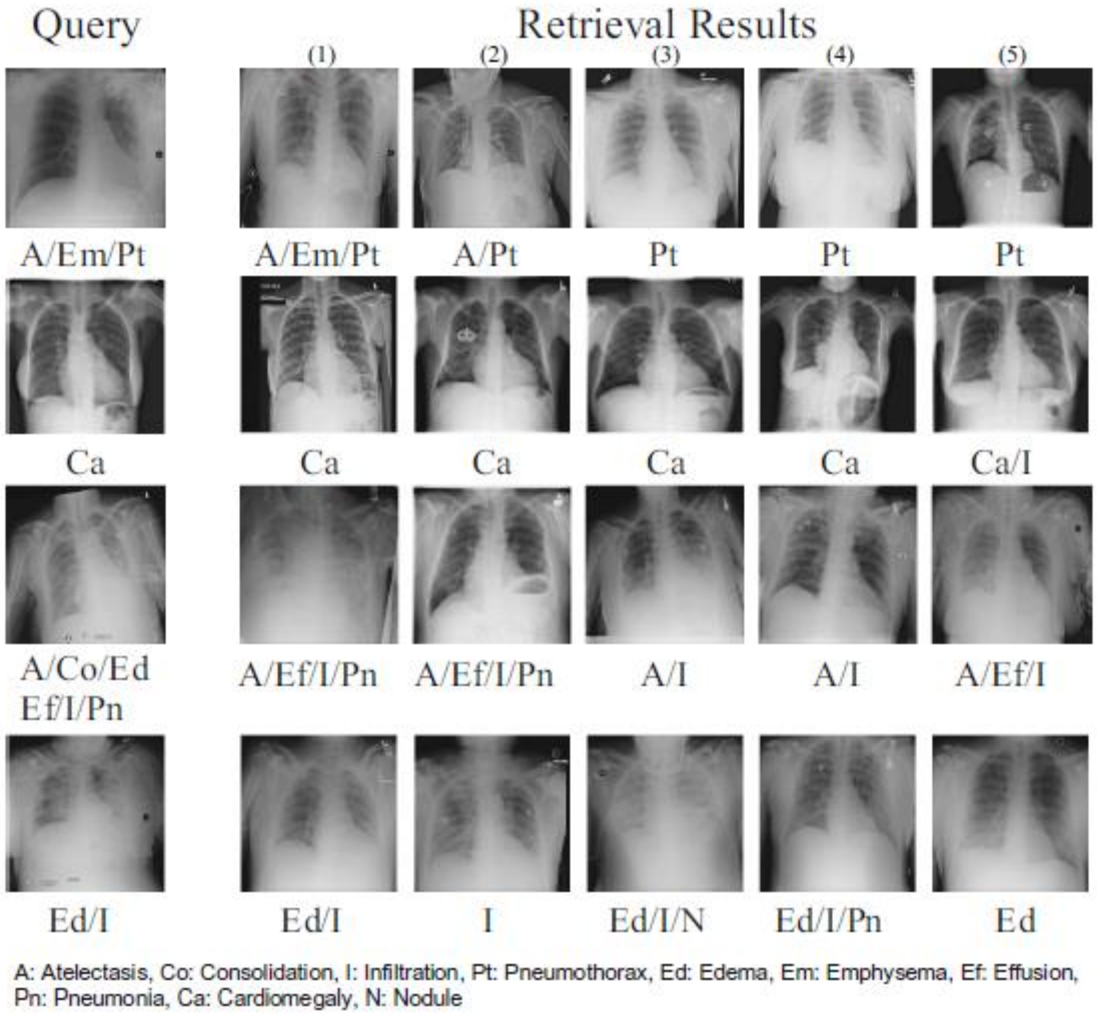


Fig. 3. Qualitative results for OSDH

Efficient Active Learning for Image Classification and Segmentation Using a Sample Selection and Conditional Generative Adversarial Network

Dwarikanath Mahapatra[1(✉)], Behzad Bozorgtabar[2], Jean-Philippe Thiran[2], and Mauricio Reyes[3]

[1] IBM Research Australia, Melbourne, Australia
dwarim@au1.ibm.com
[2] Ecole Polytechnique Federale de Lausanne, Lausanne, Switzerland
{behzad.bozorgtabar,jean-philippe.thiran}@epfl.ch
[3] University of Bern, Bern, Switzerland
mauricio.reyes@istb.unibe.ch

Abstract. Training robust deep learning (DL) systems for medical image classification or segmentation is challenging due to limited images covering different disease types and severity. We propose an active learning (AL) framework to select most informative samples and add to the training data. We use conditional generative adversarial networks (cGANs) to generate realistic chest xray images with different disease characteristics by conditioning its generation on a real image sample. Informative samples to add to the training set are identified using a Bayesian neural network. Experiments show our proposed AL framework is able to achieve state of the art performance by using about 35% of the full dataset, thus saving significant time and effort over conventional methods.

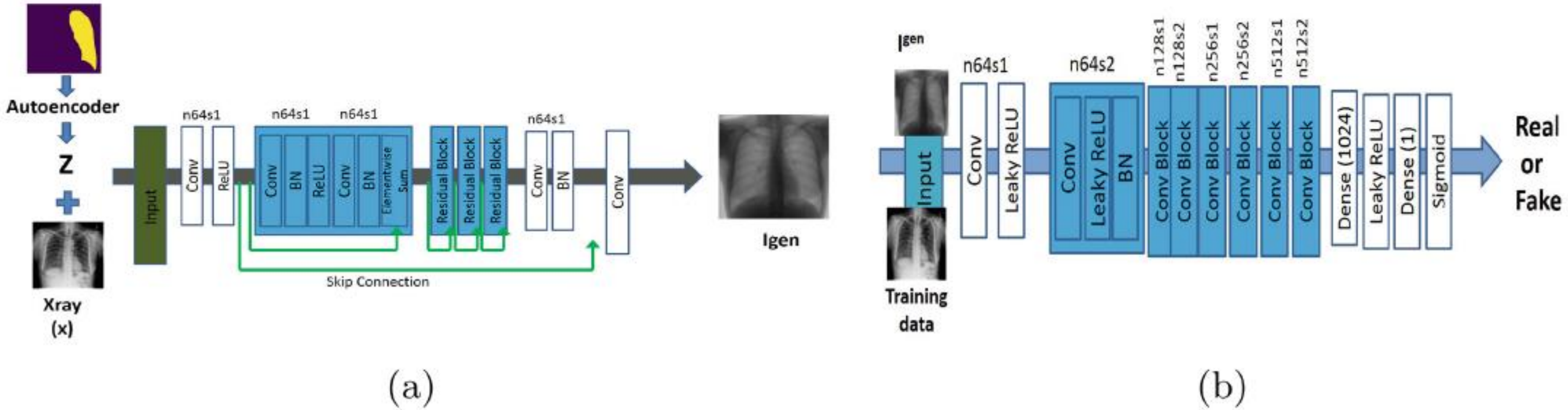


Fig. 1. (a) Generator Network; (b) Discriminator network. $n64s1$ denotes 64 feature maps (n) and stride (s) 1 for each convolutional layer.

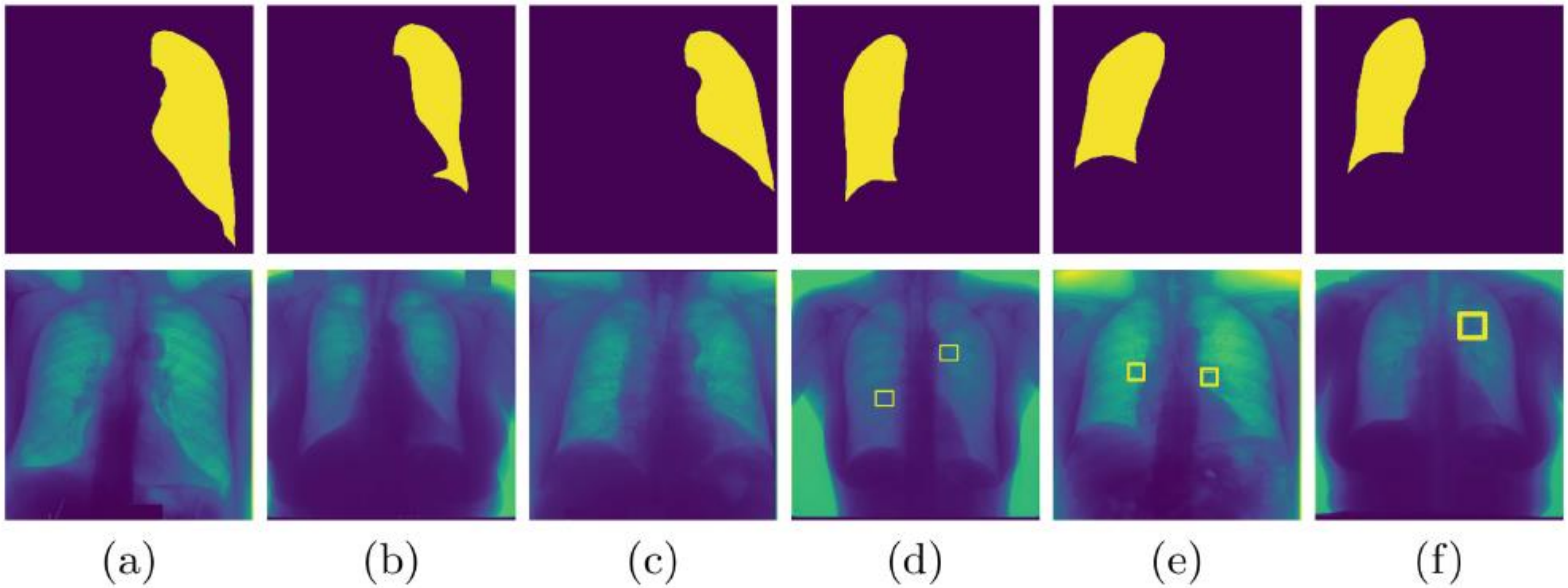


Fig. 2. Mask (Top Row 1) and corresponding informative xray image (Bottom Row); (a)–(c) non-diseased cases; (d)–(f) images with nodules of different severity at the center of yellow box. (a), (d) are the original images while others are synthetic images generated by altering the mask characteristics.

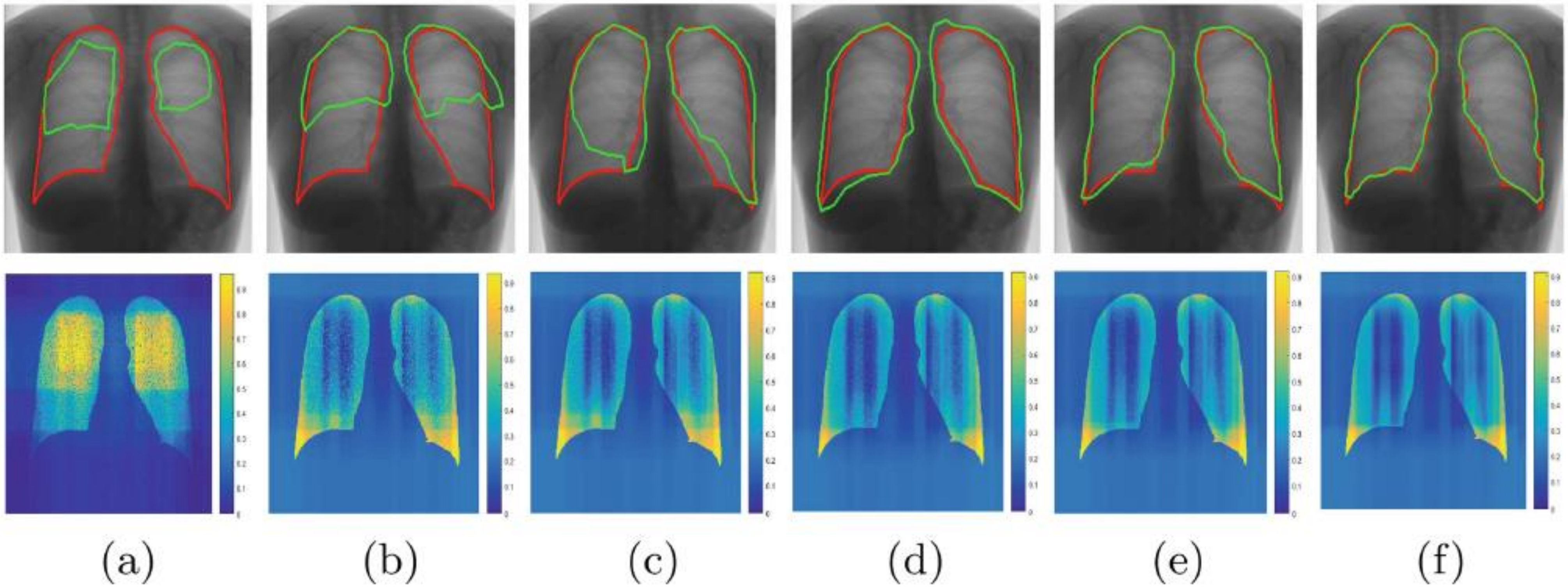


Fig. 3. Segmentation (top row) and uncertainty map (bottom row) results for different numbers of labeled examples in the training data (a) 5%; (b) 10%; (c) 20%; (d) 30%; (e) 35%; (f) 40%. Red contour is manual segmentation and green contour is the UNet generated segmentation.

Deep Active Self-paced Learning for Accurate Pulmonary Nodule Segmentation

Wenzhe Wang[1], Yifei Lu[1], Bian Wu[2], Tingting Chen[1], Danny Z. Chen[3], and Jian Wu[1(✉)]

[1] College of Computer Science and Technology, Zhejiang University, Hangzhou 310027, China
wujian2000@zju.edu.cn

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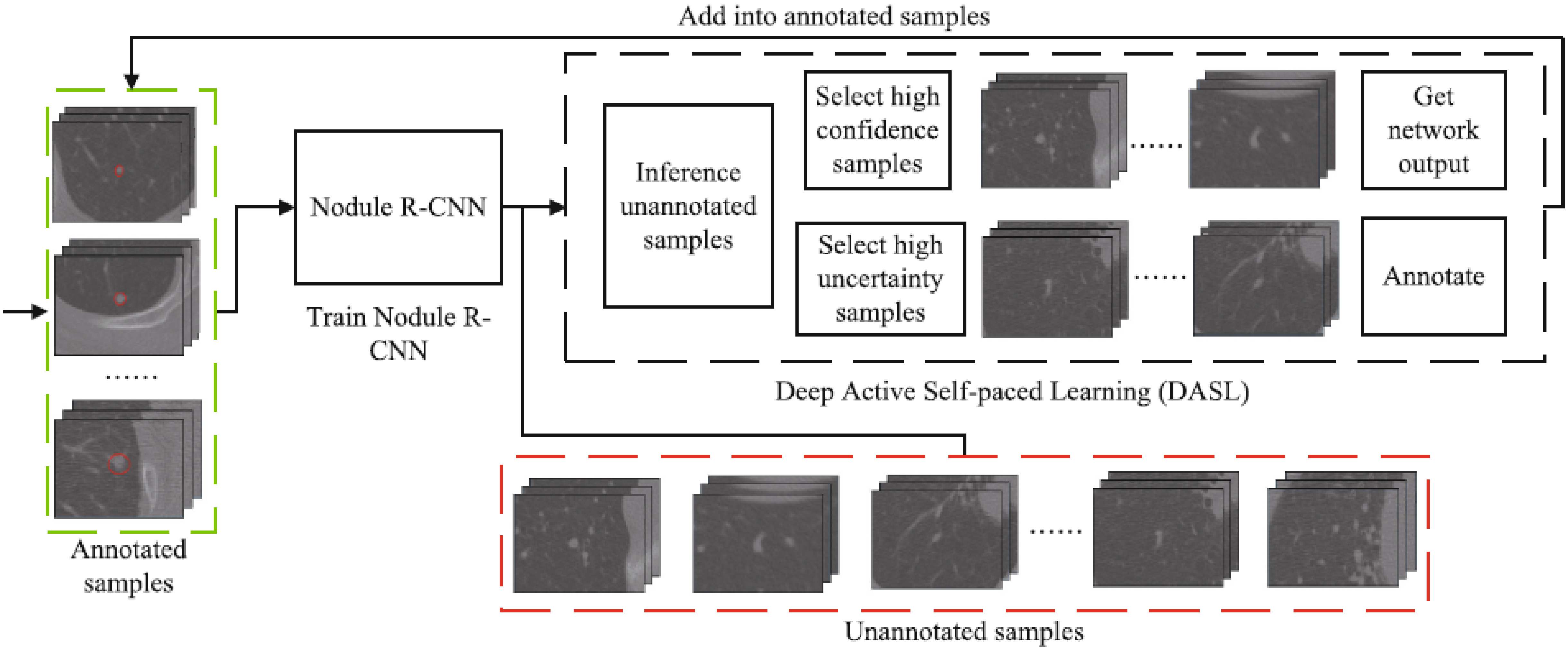
Abstract. Automatic and accurate pulmonary nodule segmentation in lung Computed Tomography (CT) volumes plays an important role in computer-aided diagnosis of lung cancer. However, this task is challenging due to target/background voxel imbalance and the lack of voxel-level annotation. In this paper, we propose a novel deep region-based network, called Nodule R-CNN, for efficiently detecting pulmonary nodules in 3D CT images while simultaneously generating a segmentation mask for each instance. Also, we propose a novel Deep Active Self-paced Learning (DASL) strategy to reduce annotation effort and also make use of unannotated samples, based on a combination of Active Learning and Self-Paced Learning (SPL) schemes. Experimental results on the public LIDC-IDRI dataset show our Nodule R-CNN achieves state-of-the-art results on pulmonary nodule segmentation, and Nodule R-CNN trained with the DASL strategy performs much better than Nodule R-CNN trained without DASL using the same amount of annotated samples.



Add into annotated samples
Nodule R-CNN
Train Nodule R-CNN
Inference unannotated samples
Select high confidence samples
Get network output
Select high uncertainty samples
Annotate
Deep Active Self-paced Learning (DASL)
Annotated samples
Unannotated samples

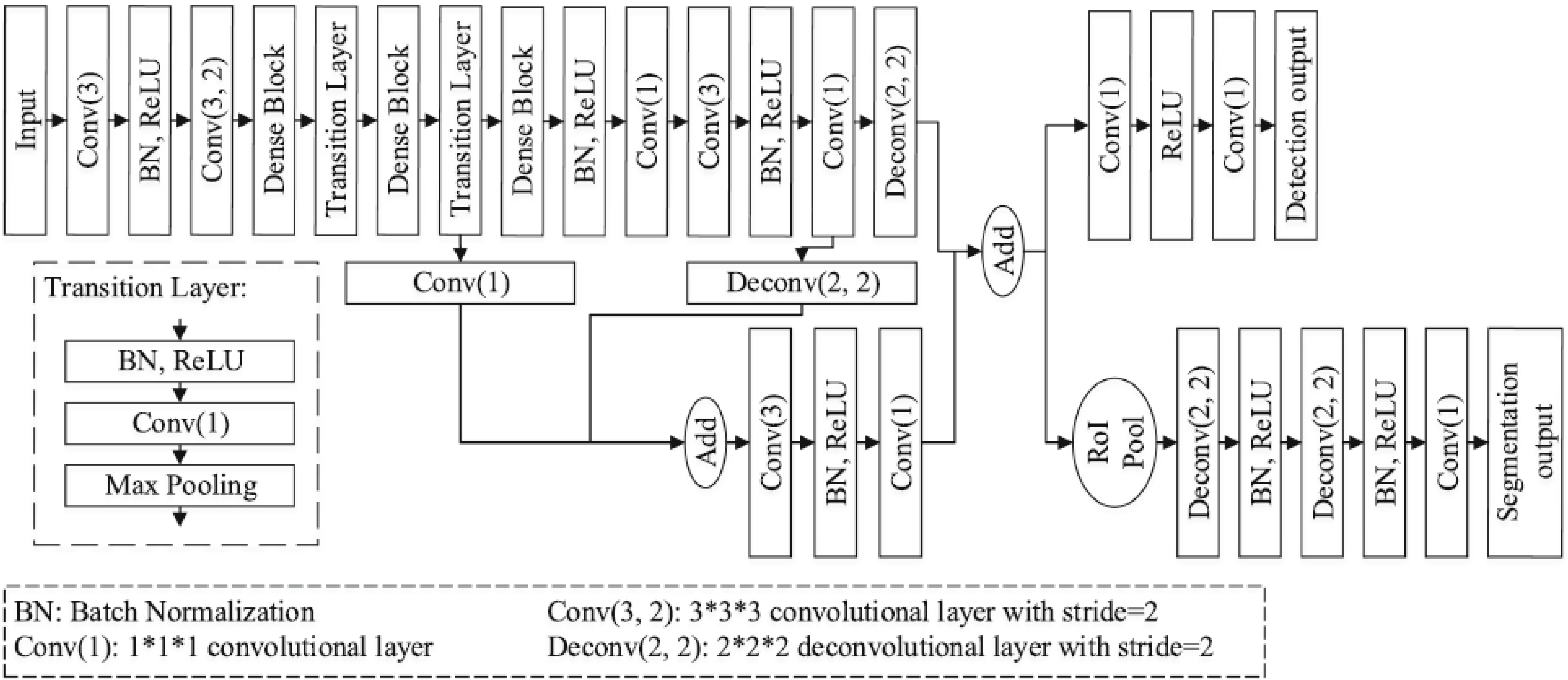


Fig. 2. The detailed architecture of our Nodule R-CNN.

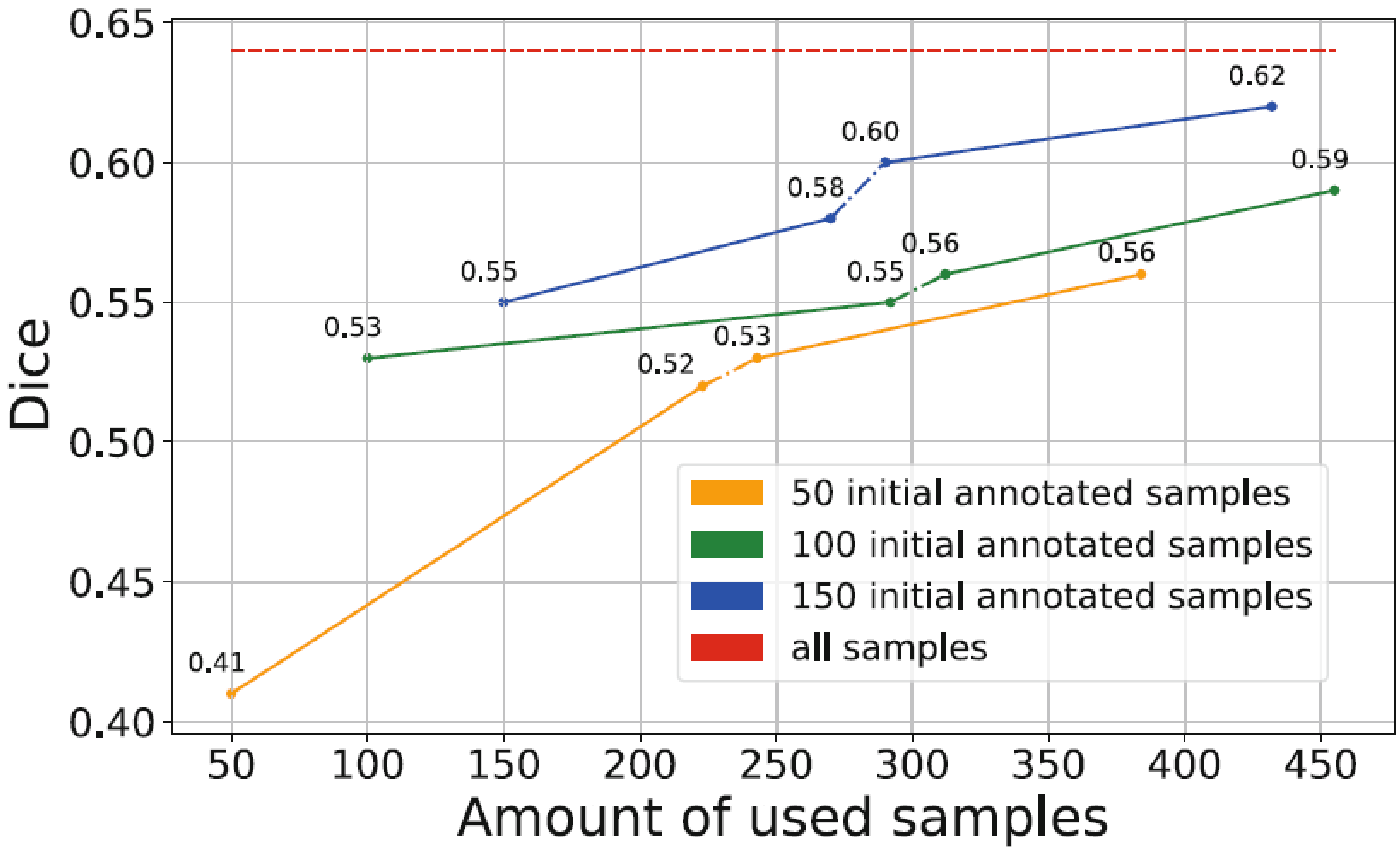


Fig. 3. Comparison using different amounts of initial annotated inputs for DASL: The solid lines are for the SPL process, the dotted lines are for the AL process, and the dashed line is for the current state-of-the-art result using full training samples.

Cost-Sensitive Active Learning for Intracranial Hemorrhage Detection

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Abstract. Deep learning for clinical applications is subject to stringent performance requirements, which raises a need for large labeled datasets. However, the enormous cost of labeling medical data makes this challenging. In this paper, we build a cost-sensitive active learning system for the problem of intracranial hemorrhage detection and segmentation on head computed tomography (CT). We show that our ensemble method compares favorably with the state-of-the-art, while running faster and using less memory. Moreover, our experiments are done using a substantially larger dataset than earlier papers on this topic. Since the labeling time could vary tremendously across examples, we model the labeling time and optimize the return on investment. We validate this idea by core-set selection on our large labeled dataset and by growing it with data from the wild.

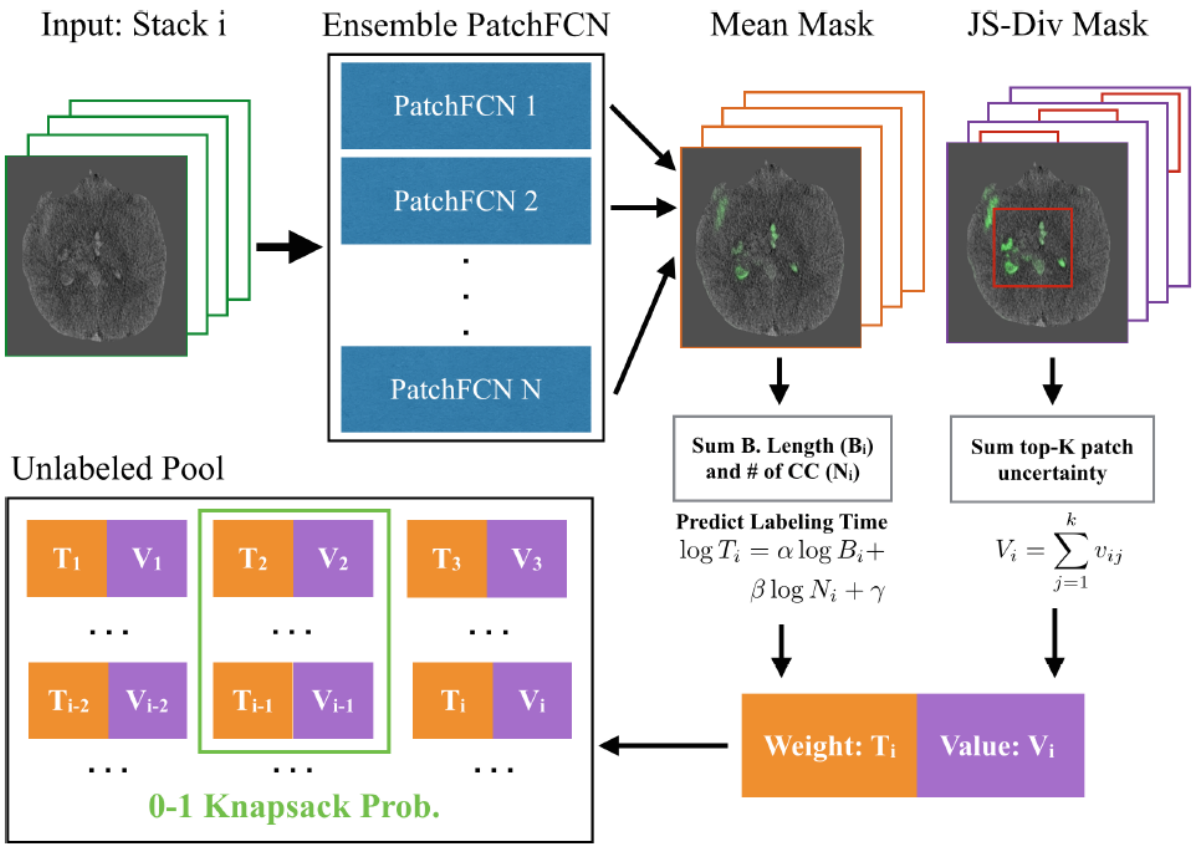

Fig. 1. Overview. First, the stack runs through the ensemble PatchFCNs trained on the seed set S, which produces the mean hemorrhage heatmap and the Jensen-Shannon (JS) divergence uncertainty heatmap. From the mean hemorrhage heatmap, we apply multiple thresholds to compute the mean boundary length B_i and number of connected components N_i. Our log-regression model then takes B_i and N_i to predict the stack labeling time T_i. The sum of uncertainty of the top-K uncertain patches is defined to be the stack uncertainty V_i. Given any fixed labeling budget(time) Q, we treat each stack in the unlabeled pool as an item of weight T_i and value V_i. The optimal set of items for annotation is obtained by solving a 0-1 Knapsack problem with dynamic programming.

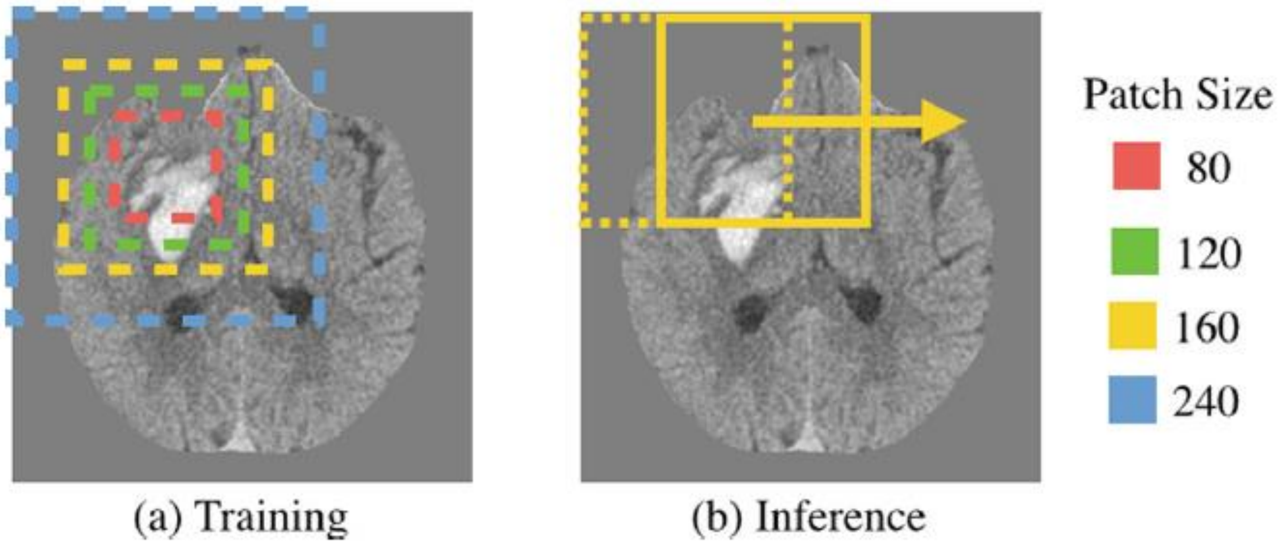

Fig. 2. PatchFCN system. We train the network on patches and test it in a sliding window fashion. The optimal crop size is found to be 160×160 for our task.