Artificial Intelligence in Medical Image Analysis:

Challenges, Methods, Applications and Beyond

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Research Focus

Algorithm

Novel machine learning methods including (semi)supervised, unsupervised, or weakly learning.

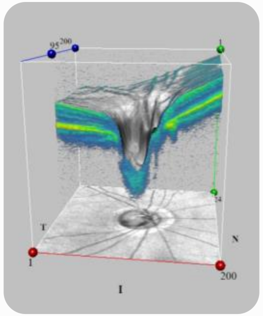
Robustness, Adaptation, and Generalization capability of AI.

Explainable AI (XAI) for interpretable and trustable healthcare, etc.

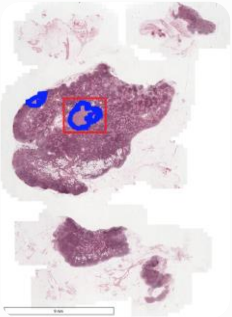
How AI-driven technologies can assist doctors and help patients ultimately?

Applications

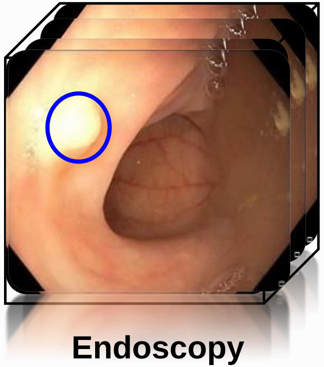
Radiology



Ophthalmology



Pathology



Endoscopy

Why Medical Image Analysis?

>10K

Human Diseases

[IDC-11, 2020]

>80%

Imaging

[EMC research from IDC]

>70%

Decision

[EMC research from IDC]

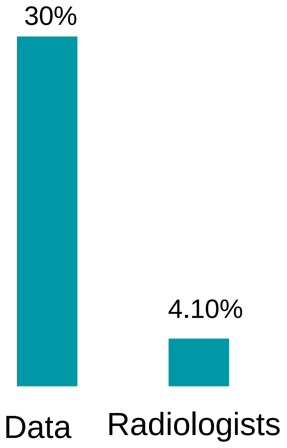
12,878

Symptoms

[Radiology Gamuts Ontology]

Shortage of Healthcare Resources

Radiology



Radiotherapy

Digital Pathology

20.6% Radiologists spend 10+ hours reading reports everyday

Radiotherapy target area outline takes 1-3 hours or more

Lacking 100K+ pathologists
15+ mins per WSI

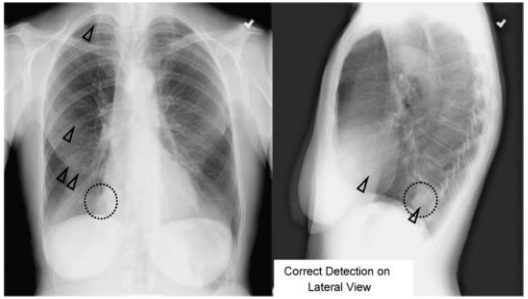
Grand View Research

Introduction

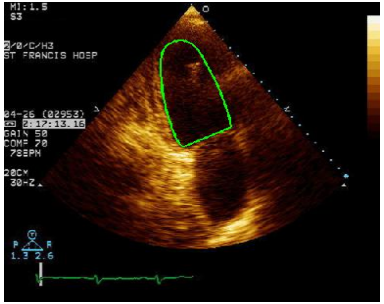
Medical Image Computing/Analysis (MIC/MIA)

Disease classification, Biomarker detection & Semantic parsing

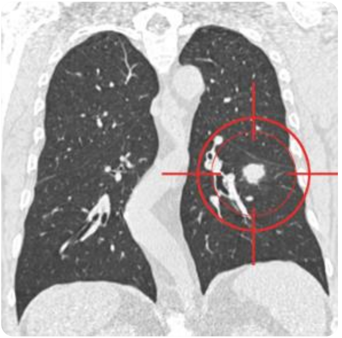
- Disease screening and triaging;
- Diagnosis and prognosis;
- Surgical planning and treatment;
- Measurements & visualization, etc.



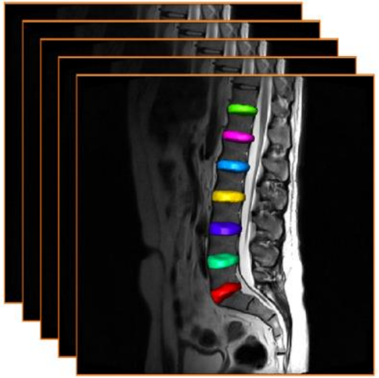
Computerized analysis of medical images in 1960s;
CADe/CADx dated back to 1980s [Kunio, CIMG, 2007]



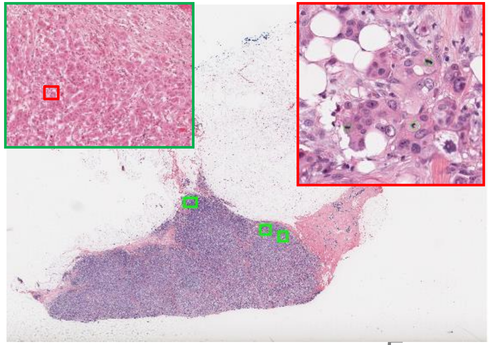
US



CT



MRI



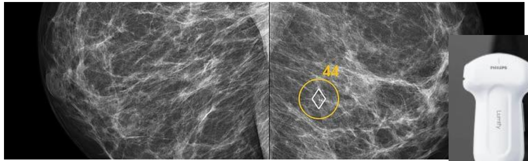
Histology

Introduction

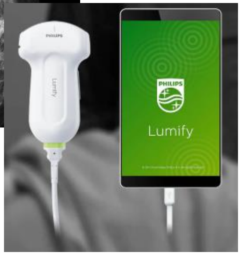
❑ DL in Medical Image Analysis

❑ FDA approved AI-based products in medicine

ScreenPoint Medical

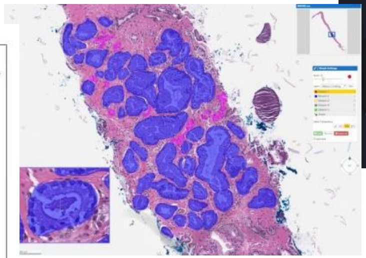


Mammogram

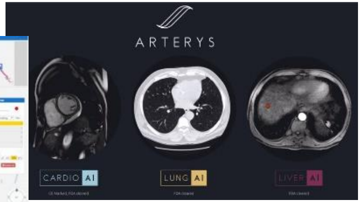


Ultrasound

Fundus



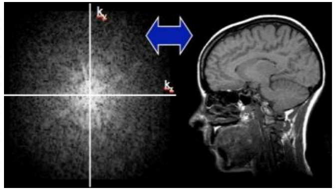
Pathology

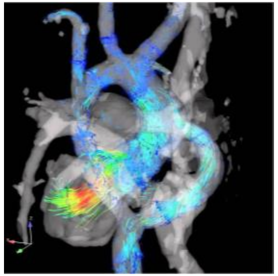


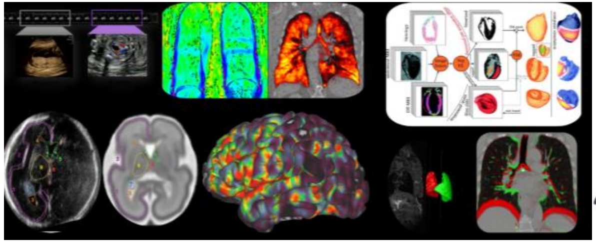
CT & MRI

AI Improves Entire Clinical Workflow

from acquisition to prognosis





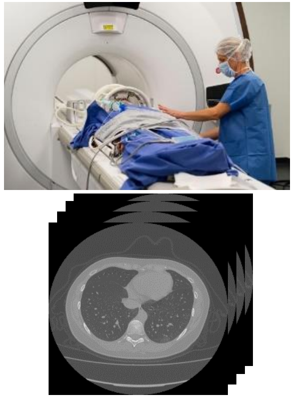


Acquisition | Reconstruction | Visualization | Analysis | Treatment & Prognosis

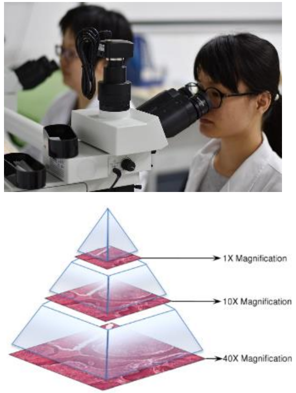
Versatile Applications

Including but definitely not limited to…

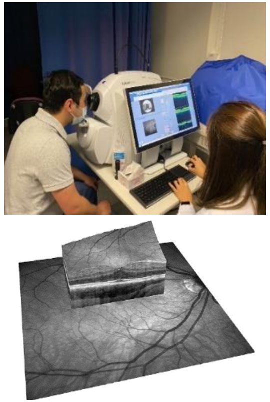
Radiology



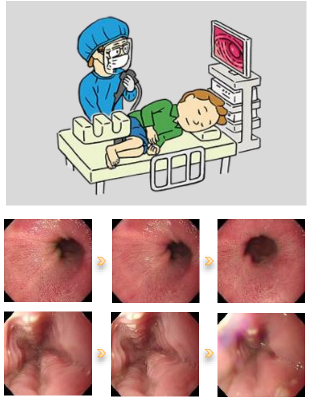
Pathology



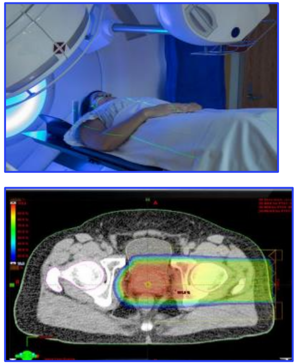
Ophthalmology



Endoscopy

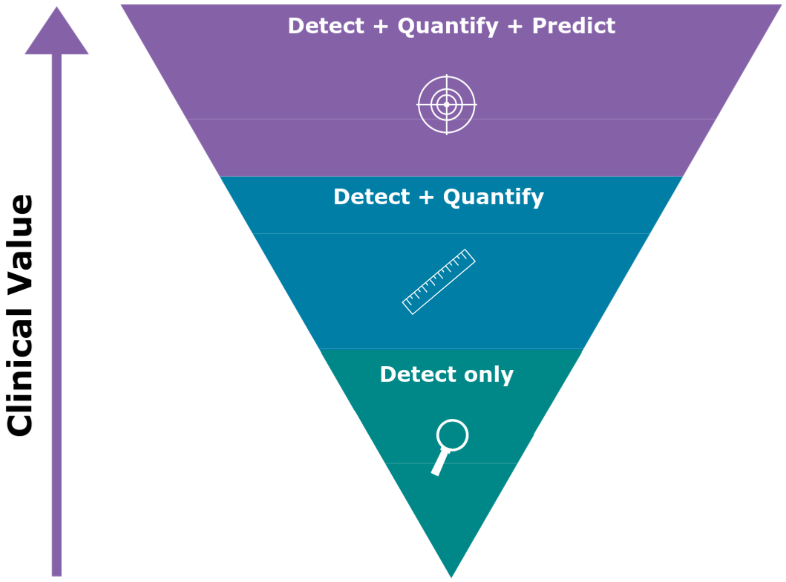


Radiotherapy



Clinical Value Chain

Clinical Value of AI Tools in Medical Imaging



Detect + Quantify + Predict

- Real-time diagnostic decision support
- Risk stratification for early detection and/or diagnosis
- Reduced need for intervention (e.g. biopsies)

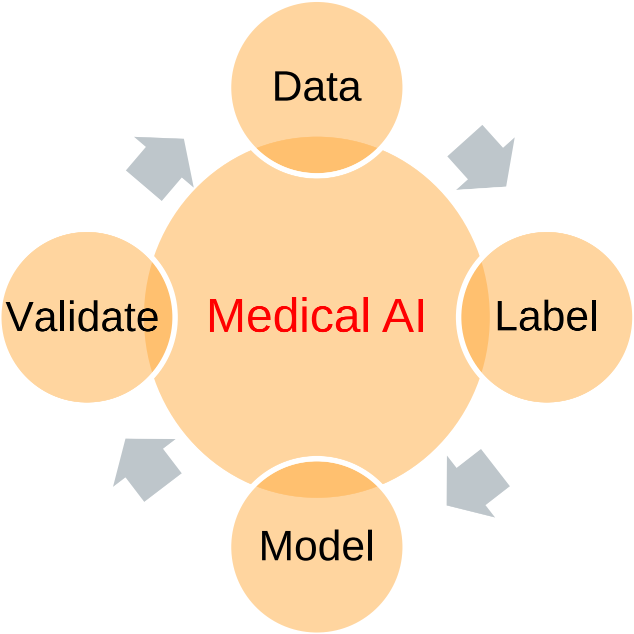
Detect + Quantify

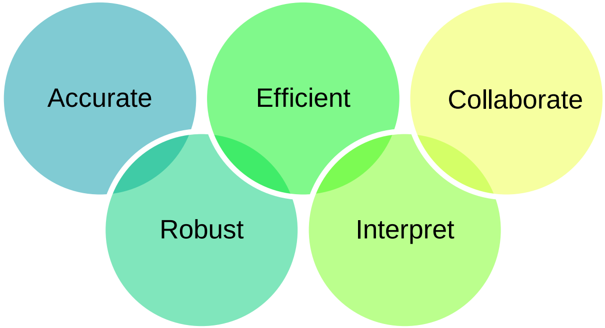
- Enhanced productivity - no manual measurements
- Improved diagnostic confidence
- Enables precision medicine (personalized treatment)

Detect Only

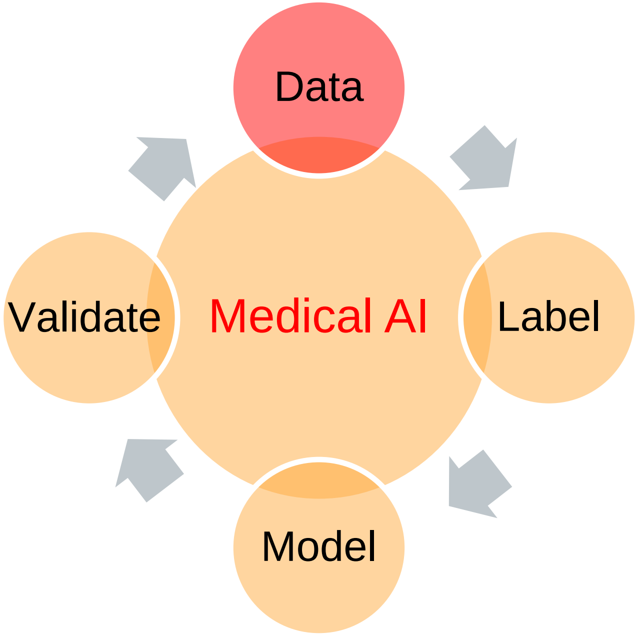
- Improved productivity
- Reduced missed diagnoses

Key Elements of Medical AI





Outline



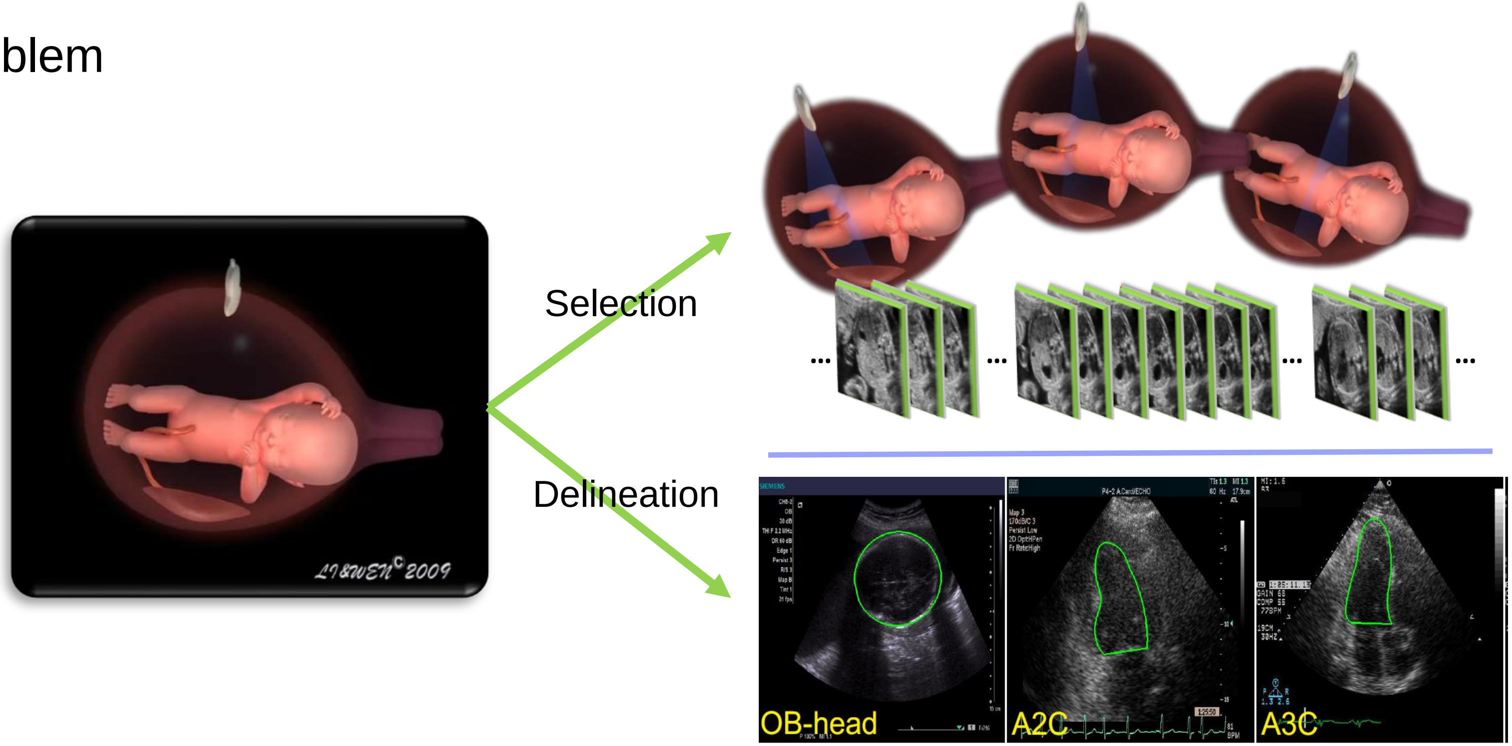
Key Challenges:

1. Limited training data vs Data hungry in DL

Intelligent Ultrasound Analysis

Intelligent Ultrasound Analysis

Problem

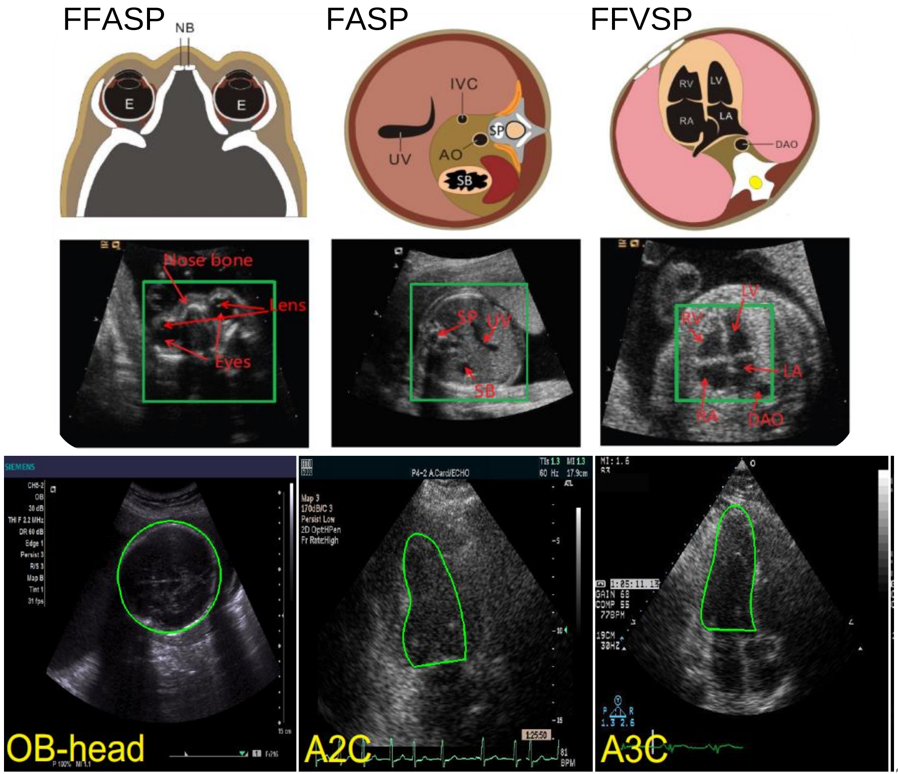


[Chen, et al. MICCAI 2015, 2016, IEEE-JBHI 2016, IEEE Cybernetics 2017, 2019 YSPIA Award]

Intelligent Ultrasound Analysis

Challenges

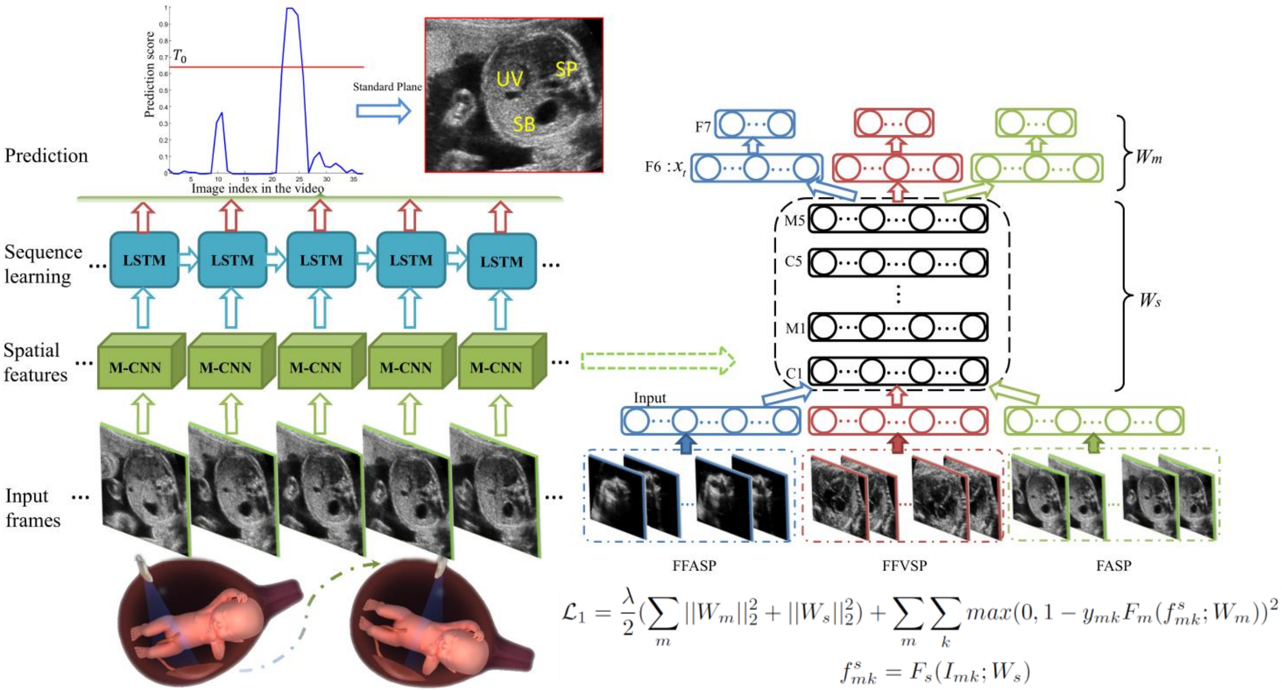
- Limited medical dataset, leading to overfitting issue
- Abounding artifacts, e.g., acoustic shadows and speckle noise
- Large intra-variation and small inter-variation due to deformation of soft tissue, vendors, et al.



[Chen, et al. MICCAI 2015, 2016, IEEE-JBHI 2016, IEEE Cybernetics 2017, 2019 YSPIA Award]

Intelligent Ultrasound Analysis

Method



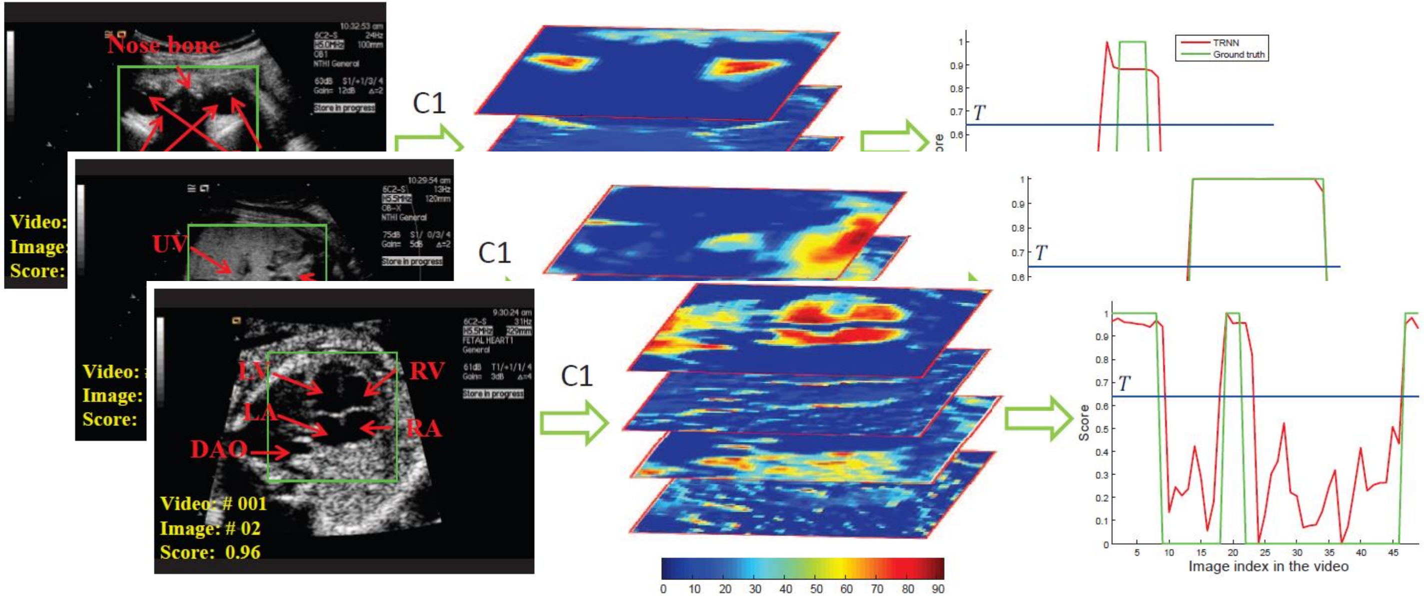
Left: Overview of the proposed T-RNN framework; right: M-CNN model.

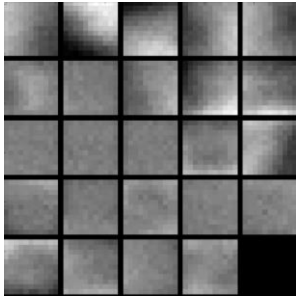
[Chen, et al. MICCAI 2015, 2016, IEEE-JBHI 2016, IEEE Cybernetics 2017, 2019 YSPIA Award]

Intelligent Ultrasound Analysis

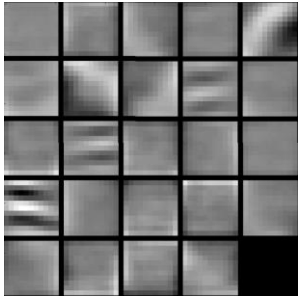
Experiments and Results

Qualitative Evaluation





R-CNN

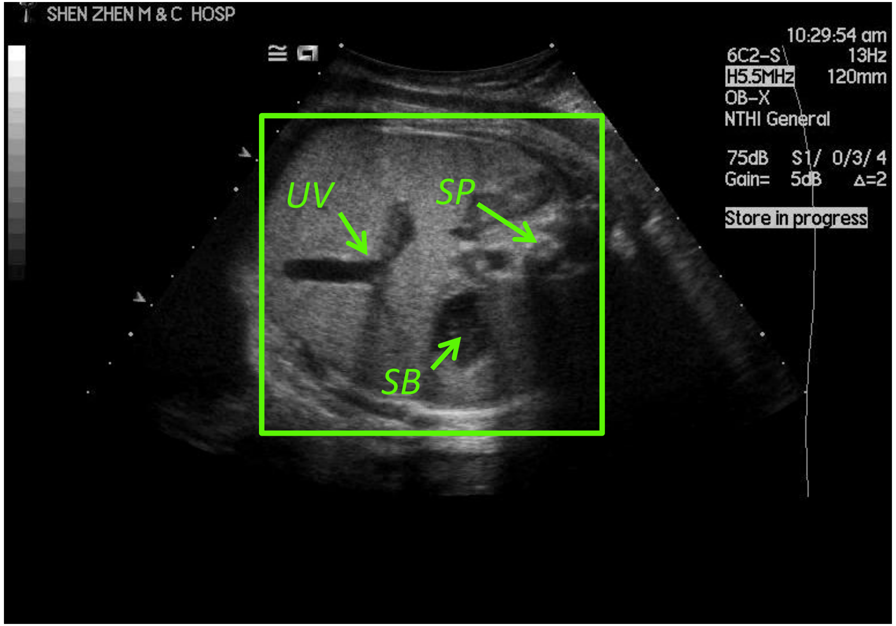


T-RNN

[Chen, et al. MICCAI 2015, 2016, IEEE-JBHI 2016, IEEE Cybernetics 2017, 2019 YSPIA Award]

Intelligent Ultrasound Analysis

Demo

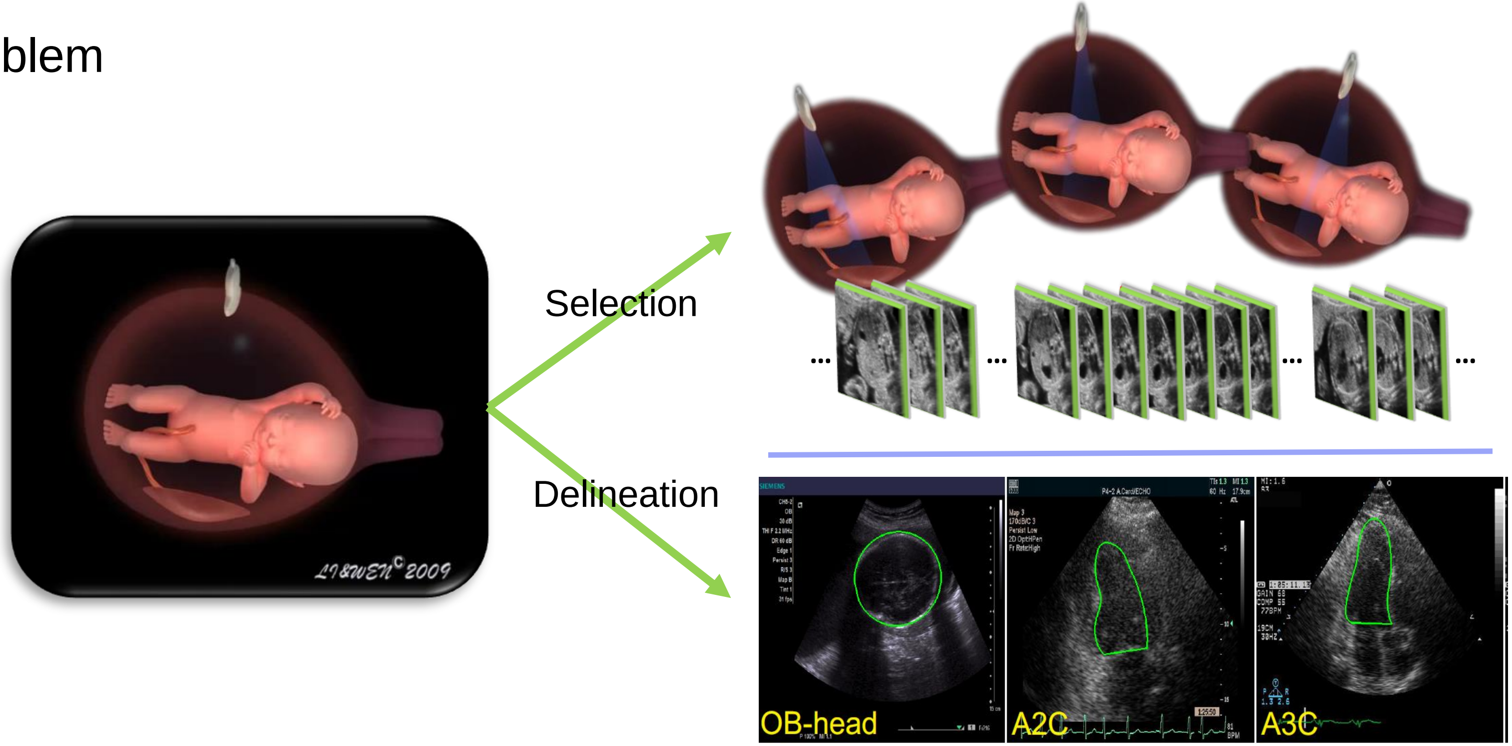


Frame : *# 25* **Detection score :** *0.99*

[Chen, et al. MICCAI 2015, 2016, IEEE-JBHI 2016, IEEE Cybernetics 2017, 2019 YSPIA Award]

Intelligent Ultrasound Analysis

Problem



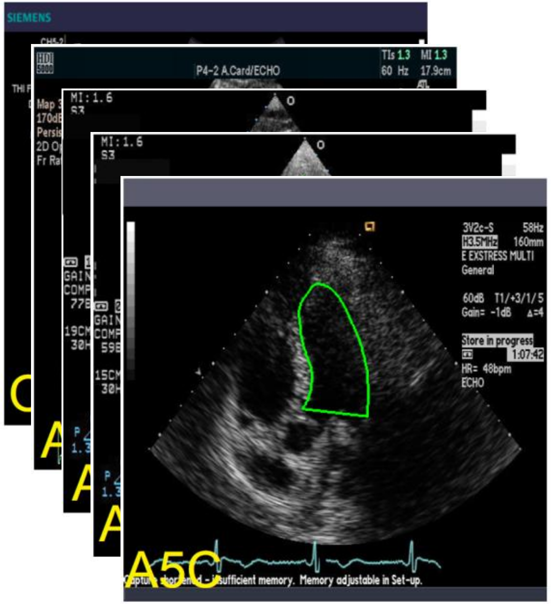
[Chen, et al. MICCAI 2015, 2016, IEEE-JBHI 2016, IEEE Cybernetics 2017, 2019 YSPIA Award]

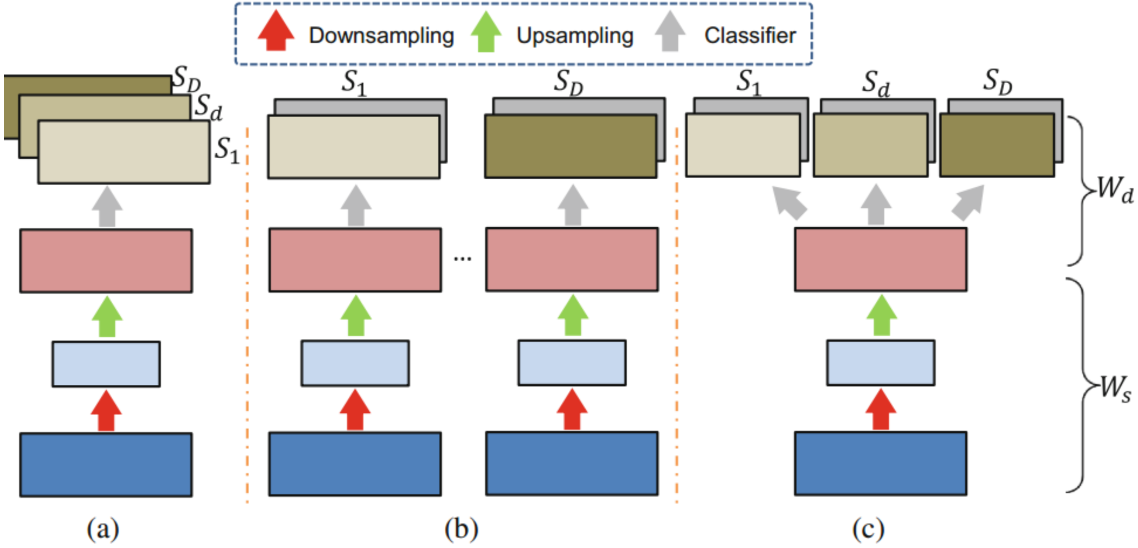
Intelligent Ultrasound Analysis

SIEMENS Healthineers

MICCAI 2016 Athens

Iterative Multi-domain Regularized DL for Structure Segmentation





$$\mathcal{L} = -\sum_{d=1}^{D}\sum_{n=1}^{N_d}\sum_{x\in I_n^d} \log p(y_x|x; W_s, W_d) + \frac{\lambda}{2}\sum_{d=1}^{D}\sum_{n=1}^{N_d}(||W_d||_2^2 + ||W_s||_2^2)$$

Intelligent Ultrasound Analysis

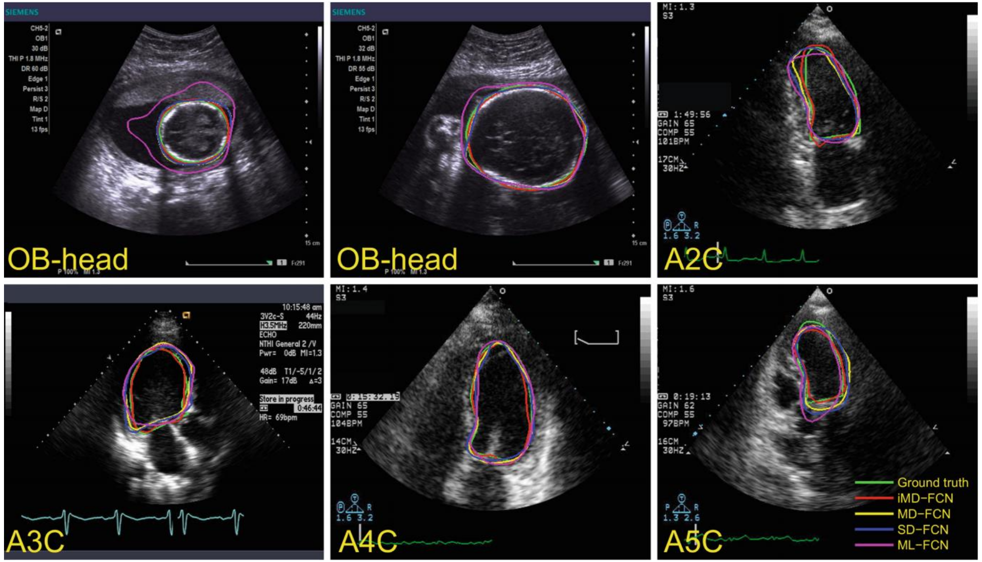
Experiments and Results

Table 3. Dataset of US Image Segmentation Largest dataset

Dataset	OB	A2C	A3C	A4C	A5C	Total
Training	1,313	9,315	8,228	12,500	3,005	34,361
Test	329	2,314	2,055	3,118	717	8,533

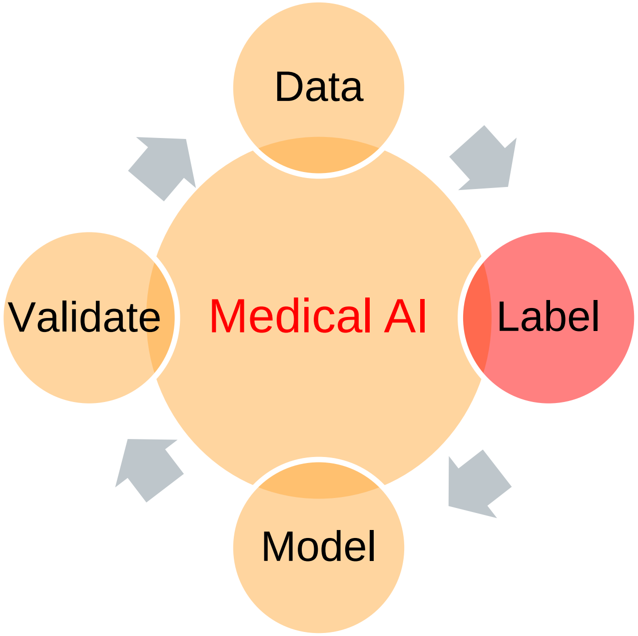
Table 4. Dice Ratio of Segmentation Results

Method	OB	A2C	A3C	A4C	A5C
ML-FCN	0.860	0.826	0.773	0.804	0.738
SD-FCN	0.942	0.851	0.811	0.833	0.768
MD-FCN	0.950	0.865	0.822	0.837	0.797
iMD-FCN	**0.961**	**0.875**	**0.864**	**0.879**	**0.891**
DGS [4]	-	0.832	-	0.844	-
Human	0.971	0.908	0.858	0.917	0.909



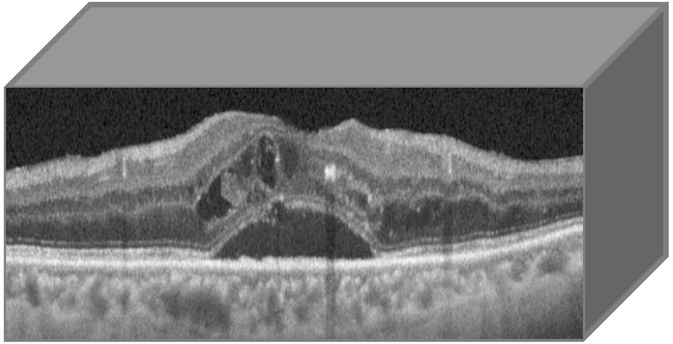
[MICCAI 2016]

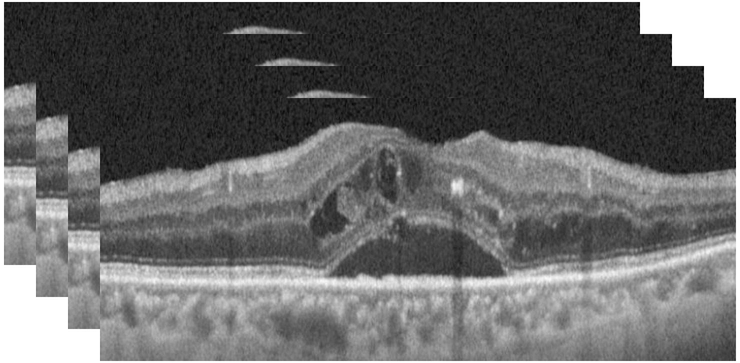
Outline



Key Challenges:

1. Imperfect labels with weak annotation.





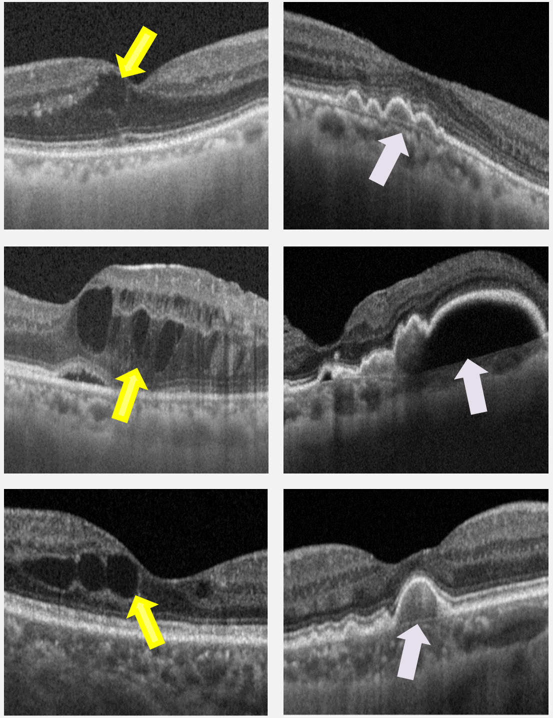
Weak annotation: What is given, but where is missing.

Problem

- Diabetic macular edema (DME) and age-related macular degeneration (AMD) are two common macula-related diseases.
  - irreversible visual loss and blindness.
  - early detection and timely treatment are important.
- Challenges of manual assessment:
  - huge workload & time-consuming
  - subjective, error-prone
  - shortage of ophthalmologists

Automated 3D OCT image classification

DME vs AMD

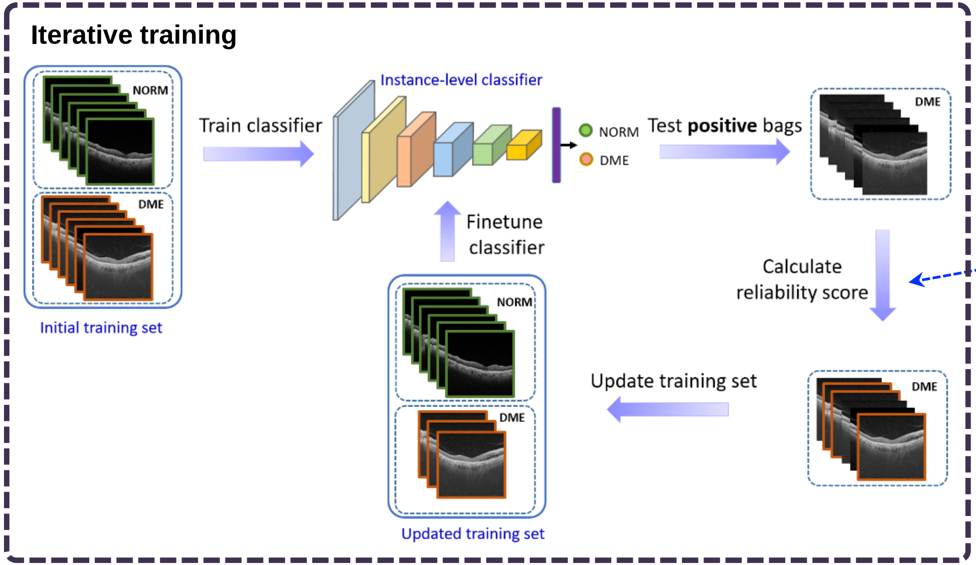


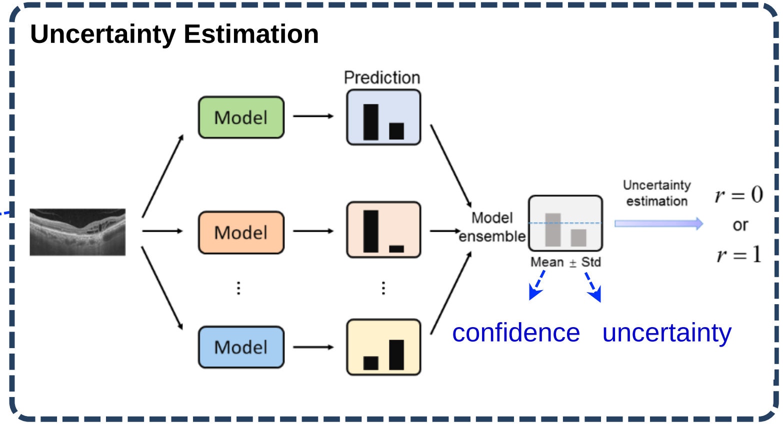
Optic coherence tomography (OCT)

Proposed method

- Instance-level classifier under UD-MIL
  - Identify **discriminative** instances
  - Abstract representative **features**

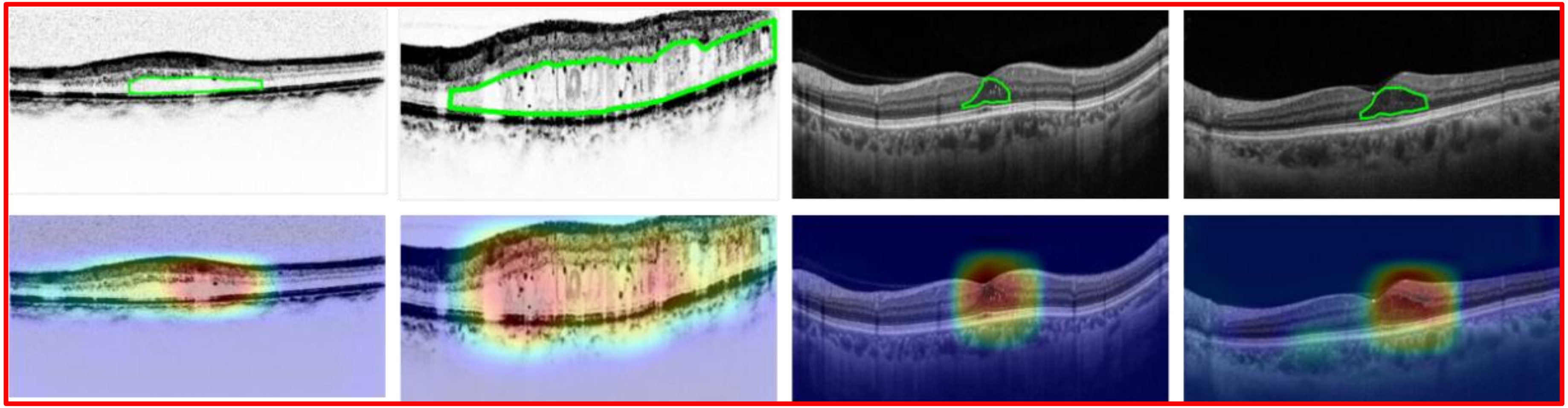
Bags	**Instances**	**Reliability scores**
$X = \left\{X^t\right\}_{t=1}^{T}$	$X^t = \{x_i^t\}_{i=1}^{n_t}$	$R^t = \{r_i^t\}_{i=1}^{n_t}$





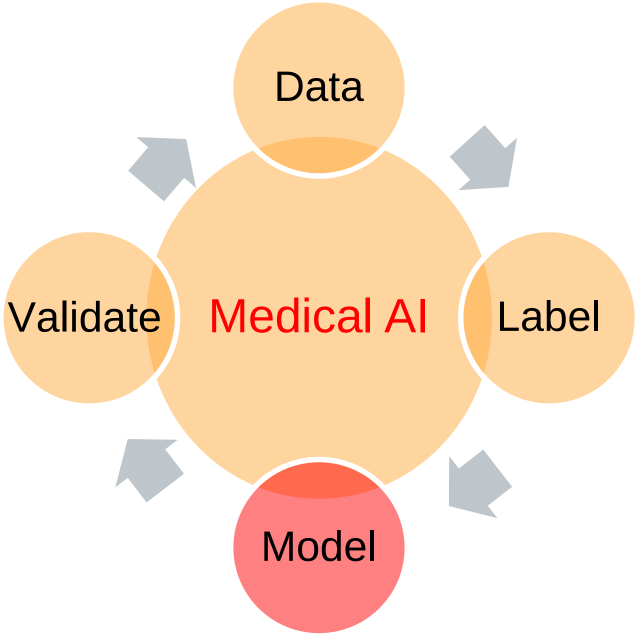
Experiments

❑ Results



Class activation map obtained by UD-MIL model

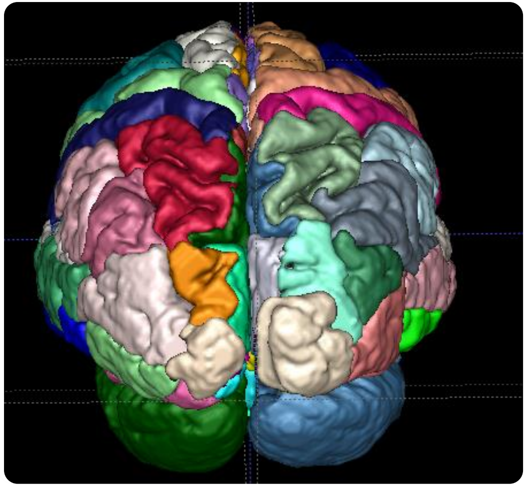
Outline



Key Challenges:

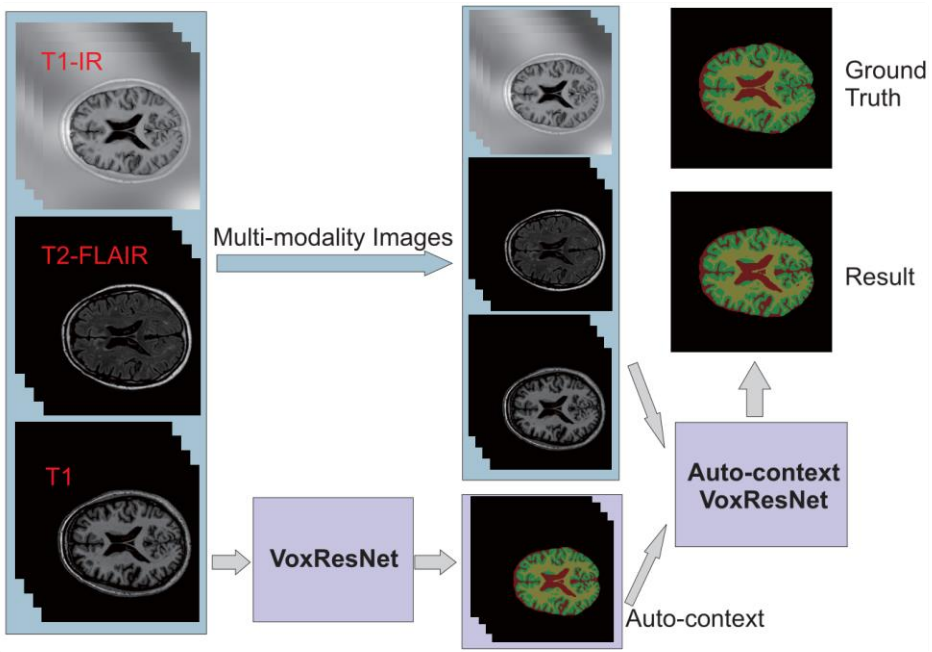
1. Robust semantic understanding of volumetric structures.

VoxResNet for Brain Segmentation



VoxResNet for Brain Segmentation

VoxResNet with Multi-modality & Auto-Context [Tu, TPAMI 2010]



[Chen, et al. NeuroImage 2018 Most Cited Articles]

VoxResNet for Brain Segmentation

Experiments and Results

Table II: Results of MICCAI MRBrainS Challenge of different methods (DC: %, HD: mm, AVD: %. only top 10 teams are shown here).

Method	GM			WM			CSF			Score*
	DC	HD	AVD	DC	HD	AVD	DC	HD	AVD	
CU_DL (ours)	**86.12**	**1.47**	6.42	**89.39**	**1.94**	**5.84**	83.96	2.28	7.44	**39**
CU_DL2 (ours)	**86.15**	**1.45**	6.60	**89.46**	**1.94**	6.05	**84.25**	2.19	7.69	**39**
MDGRU	85.40	1.55	6.09	88.98	2.02	7.69	84.13	2.17	7.44	57
PyraMiD-LSTM2	84.89	1.67	6.35	88.53	2.07	5.93	83.05	2.30	7.17	59
FBI/LMB Freiburg [6]	85.44	1.58	6.60	88.86	1.95	6.47	83.47	2.22	8.63	61
IDSIA [32]	84.82	1.70	6.77	88.33	2.08	7.05	83.72	**2.14**	7.09	77
STH	84.77	1.71	**6.02**	88.45	2.34	7.67	82.77	2.31	**6.73**	86
ISI-Neonatology [22]	85.77	1.62	6.62	88.66	2.07	6.96	81.08	2.65	9.77	87
UNC-IDEA [38]	84.36	1.62	7.04	88.68	2.06	6.46	82.81	2.35	10.5	90
MNAB2 [24]	84.50	1.70	7.10	88.04	2.12	7.74	82.30	2.27	8.73	109

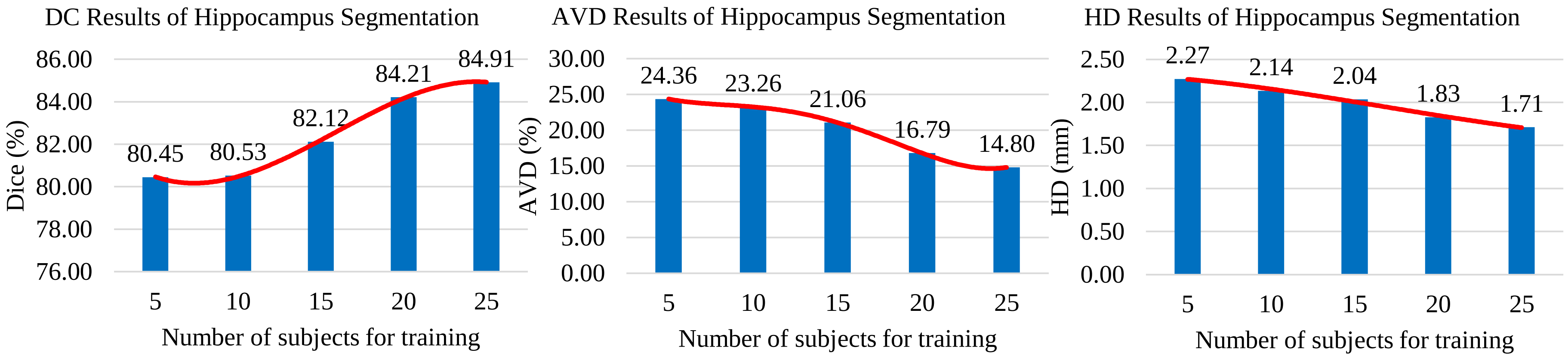
*Score = Rank DC + Rank HD + Rank AVD; a smaller score means better performance.

More results http://mrbrains13.isi.uu.nl/details.php

[Chen, et al. NeuroImage 2018 Most Cited Articles]

VoxResNet for Brain Segmentation

Application to Hippocampus Segmentation

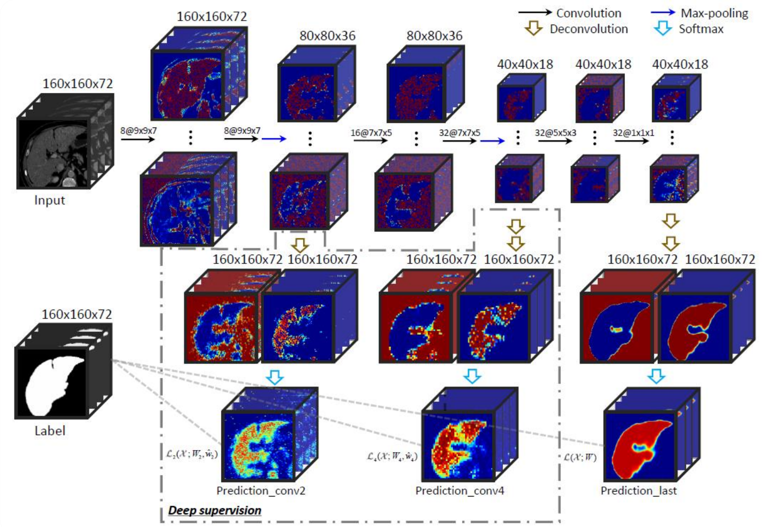


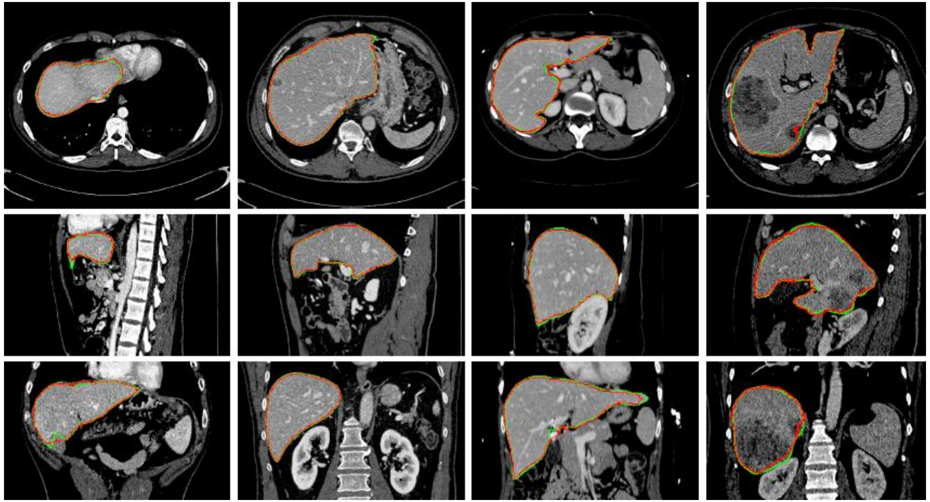
OASIS project http://www.oasis-brains.org/

www.cse.cuhk.edu.hk/~hchen/research/seg_brain.html

[Chen, et al. NeuroImage 2018 Most Cited Articles]

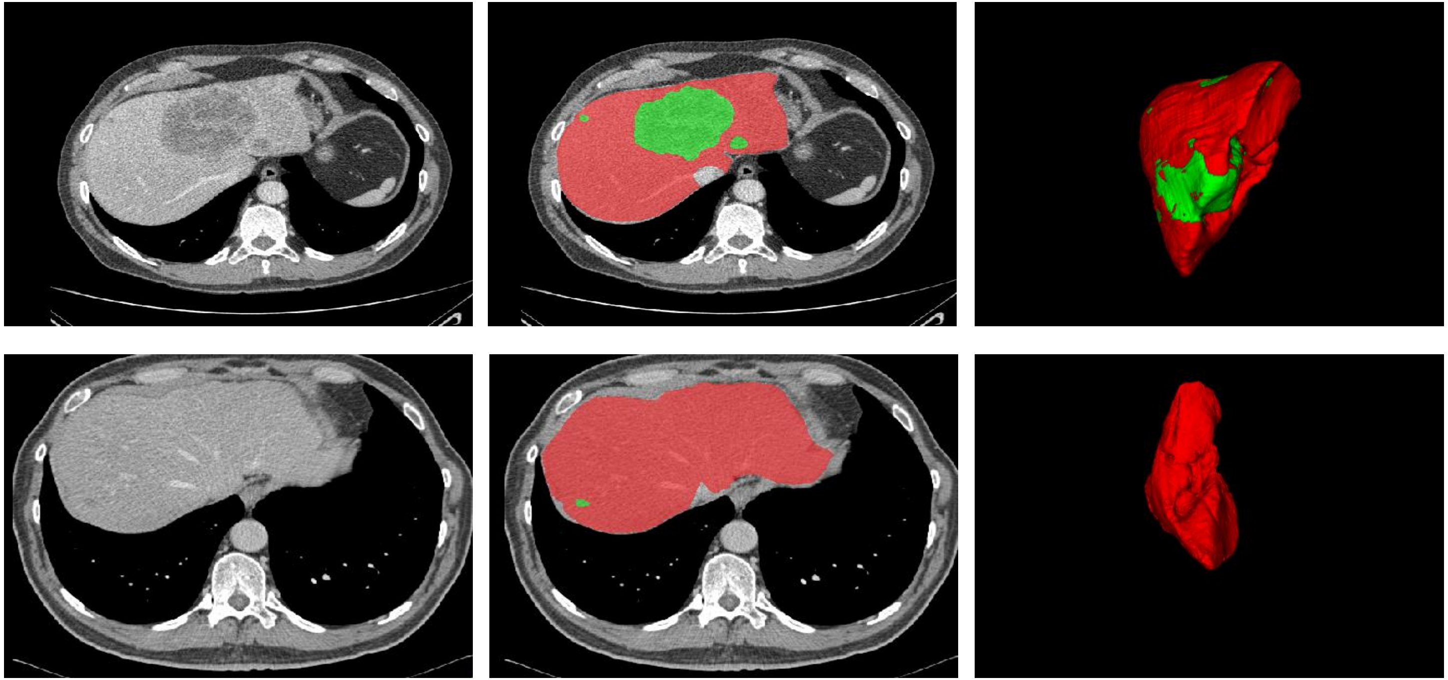
Liver Segmentation with 3D Deeply Supervised Networks





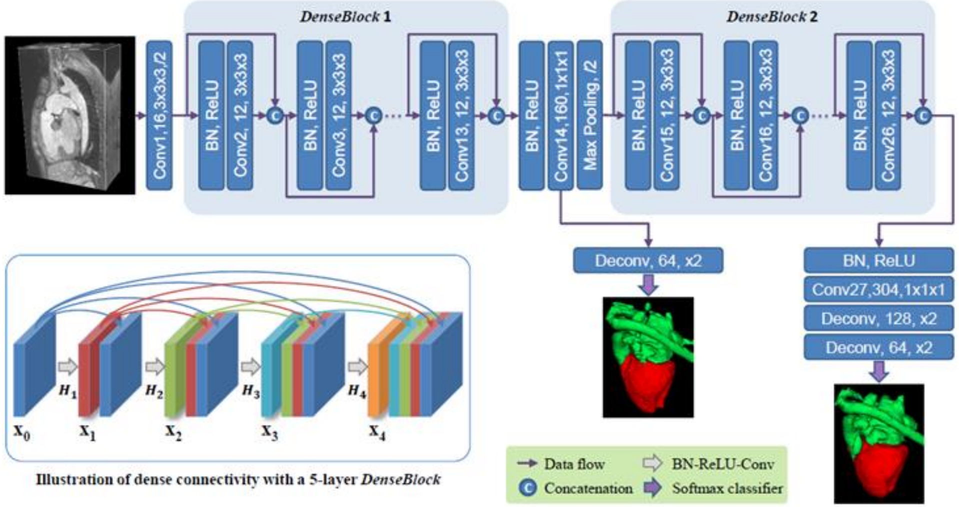
[Dou, Chen*, et al. MICCAI 2016, 2017 MICCAI-MIA Best Paper Award, 2016 MICCAI Young Scientist Award Finalist]

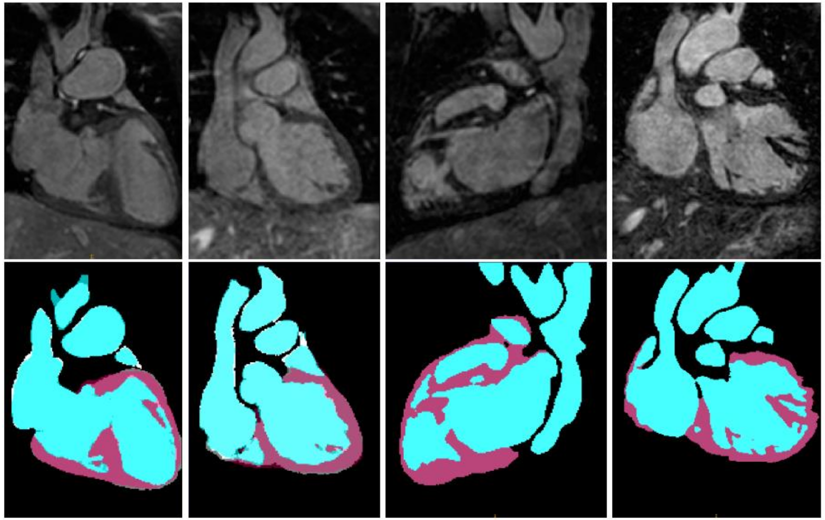
H-DenseUnet for Liver Tumor Segmentation



[Li, Chen*, et al. IEEE-TMI 2018, ESI Highly Cited Paper]

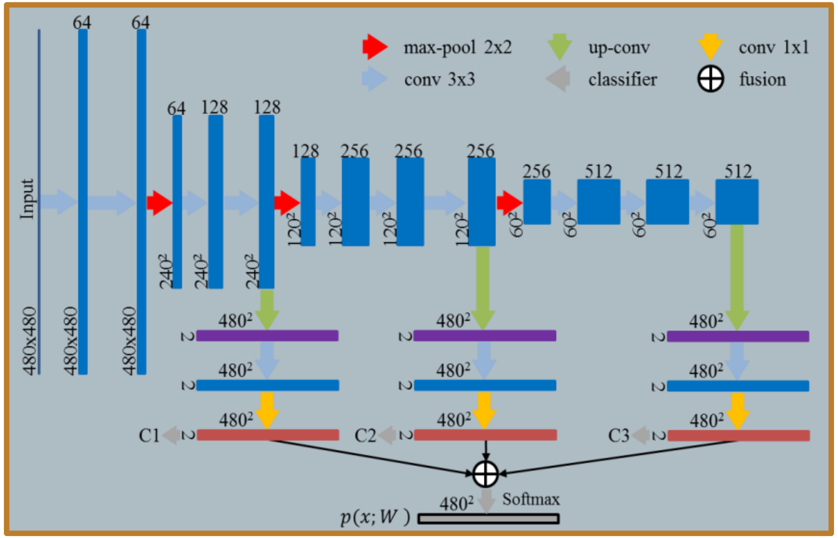
DenseVoxNet for Cardiovascular MR Segmentation

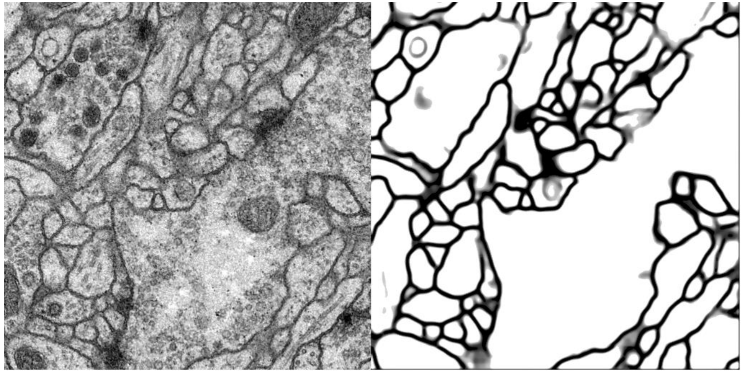


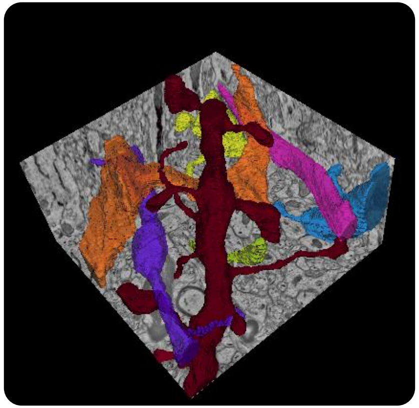


[Yu, Chen*, et al. MICCAI 2017]

ContextNet for Neuronal Structure Segmentation



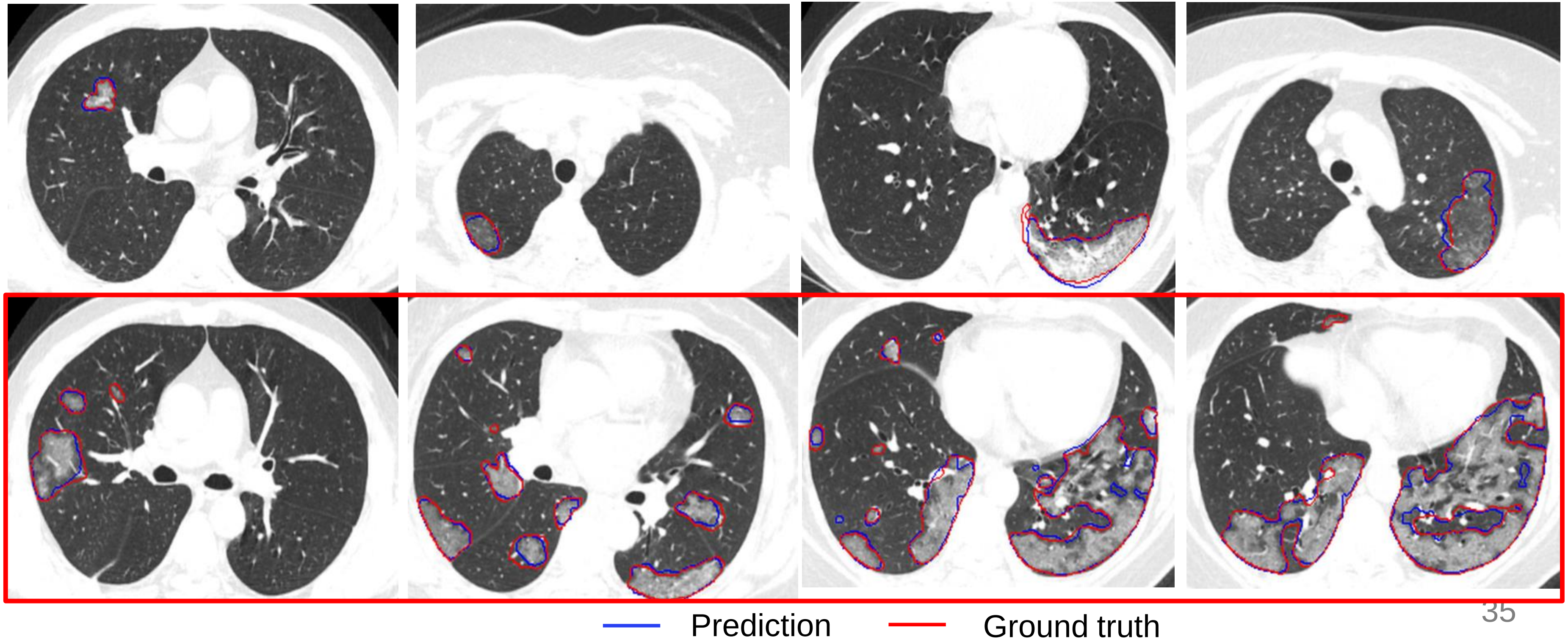


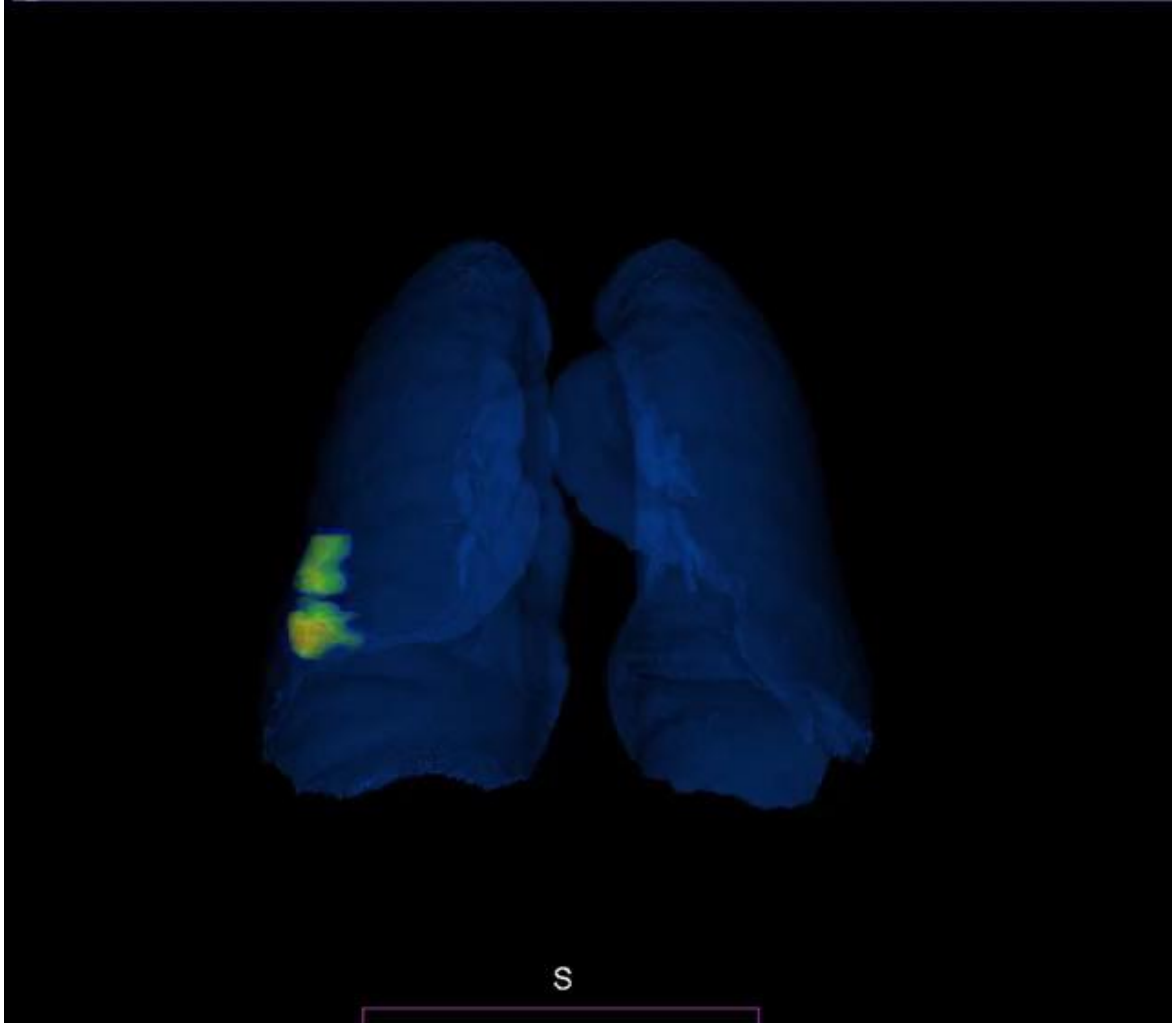


[Chen, et al. AAAI 2016 Student Travel Award]

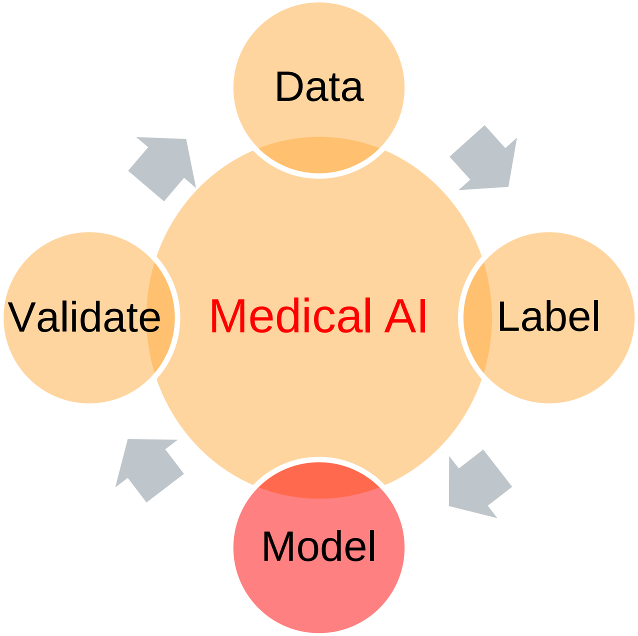
Other Scenarios in Robust Semantic Understanding of Volumetric Structures

Covid-19 CT Lesion Segmentation for Quantitative Evaluation




S

Outline

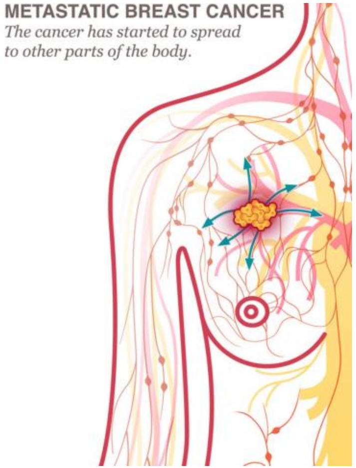


Key Challenges:

1. Robust and efficient semantic understanding of volumetric structures.
2. Scalable inference in morphology profiling.

Scalable Computational Pathology for Morphology Profiling

Fast Scannet for Breast Cancer Metastasis Detection from WSIs

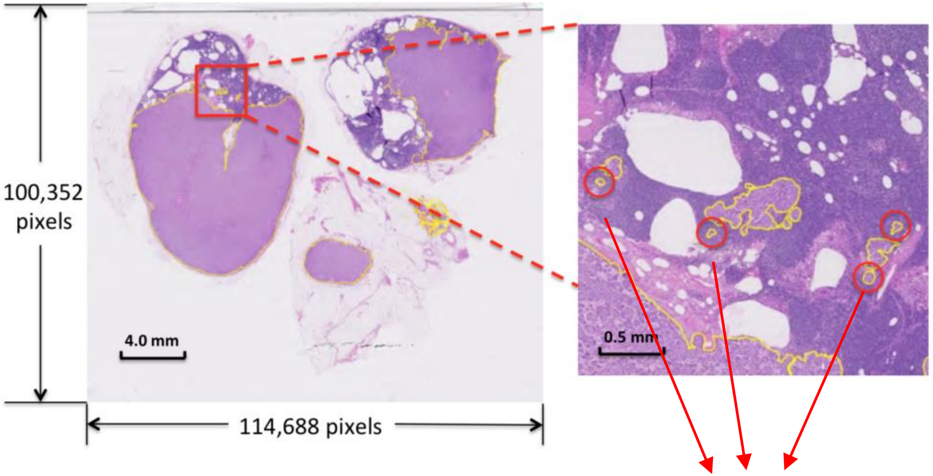


Breast Cancer Metastasis Detection

Problem

Metastasis Detection

- ❑ Breast cancer is one of leading killers among women.
- ❑ Underarm lymph nodes are the first place breast cancer likely to spread
- ❑ An important diagnostic indicator for cancer stage evaluation



Tiny metastases are easily neglected

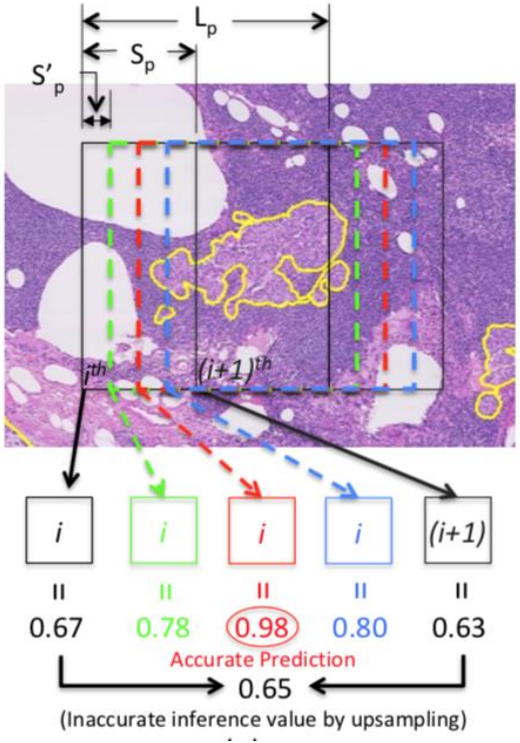
[Lin, Chen*, et al. JAMA 2017, WACV 2018, TMI 2019]

Breast Cancer Metastasis Detection

Motivation

Dense Scanning

- ❑ CNN can achieve more accurate predictions on tiny lesions by offset



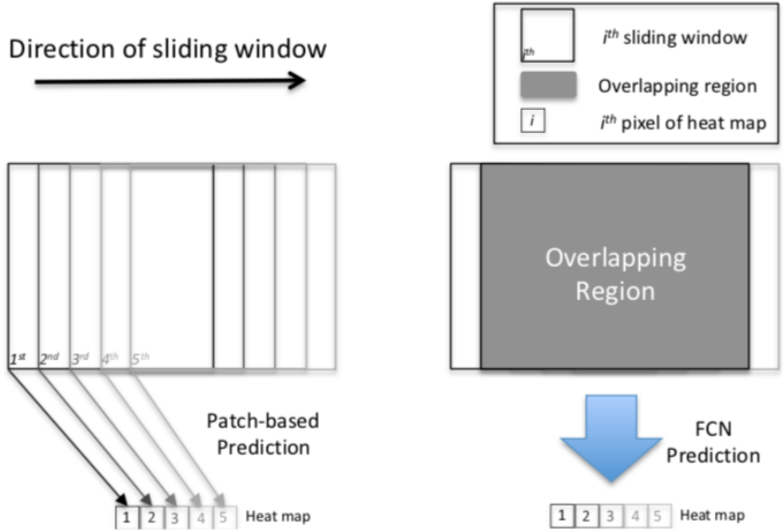
[Lin, Chen*, et al. JAMA 2017, WACV 2018, TMI 2019]

Breast Cancer Metastasis Detection

Motivation

Dense Scanning

- ❑ CNN can achieve more accurate predictions on tiny lesions by offset
- ❑ Computational redundant leads to low efficiency



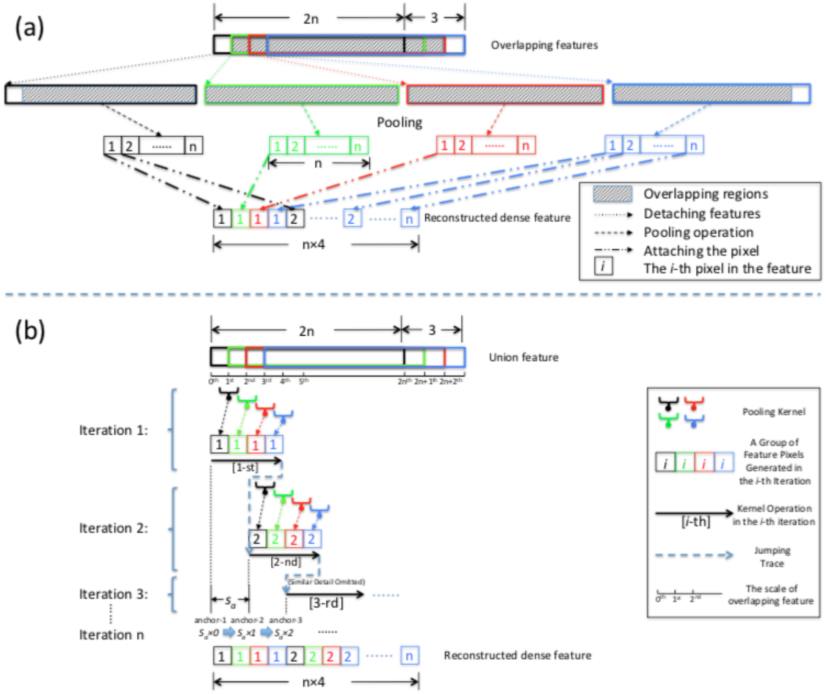
[Lin, Chen*, et al. JAMA 2017, WACV 2018, TMI 2019]

Breast Cancer Metastasis Detection

Motivation

Dense Scanning

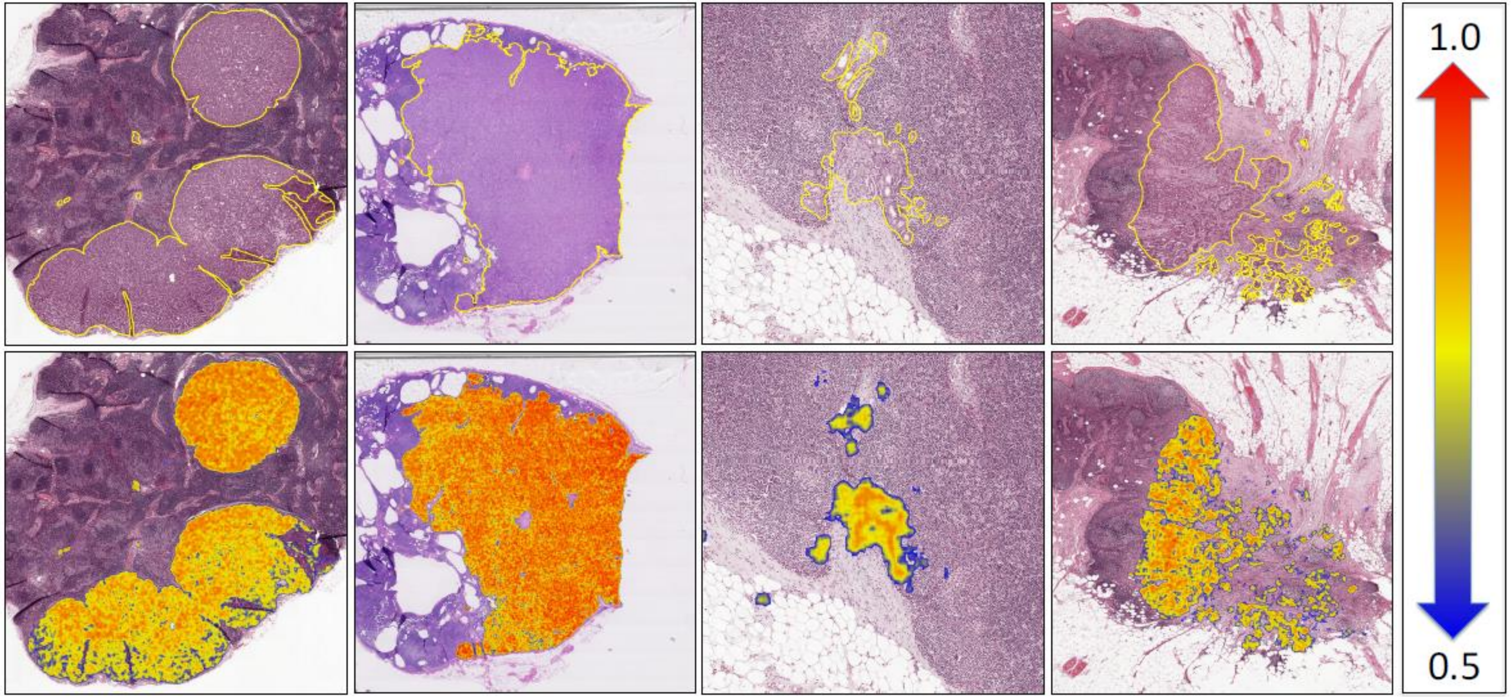
- ❑ CNN can achieve more accurate predictions on tiny lesions by offset
- ❑ Computational redundant leads to low efficiency
- ❑ With FCN architecture, iterative anchor layer is proposed for efficiency inference



[Lin, Chen*, et al. JAMA 2017, WACV 2018, TMI 2019]

Breast Cancer Metastasis Detection

Experiments and Results



[JAMA 2017, WACV 2018, TMI 2019]

Breast Cancer Metastasis Detection

Experiments and Results

QUANTITATIVE COMPARISON WITH OTHER METHODS

Methods	FROC score	AUC score
Human performance	0.7325	0.9660
Fast ScanNet-16(ours)	**0.8533**	0.9875
HMS and MIT	0.8074	**0.9935**
HMS, Gordan Center, MGH	0.7600	0.9763
Radboud Uni. (DIAG)	0.5748	0.7786
EXB Research co.	0.5111	0.9156
Middle East Tech. Uni.	0.3889	0.8642
University of Toronto	0.3822	0.8149
DeepCare Inc	0.2439	0.8833
NLP LOGIX co. USA	0.3859	0.8298
ScanNet-32(w/o HNM)	0.7030	0.9415
ScanNet-32 [48]	0.8133	0.9669

Compare with human

Compare with the state-of-the-art

With/without Anchor Layer

Localization task

Classification task

[JAMA 2017, WACV 2018, TMI 2019]

Breast Cancer Metastasis Detection

Experiments and Results

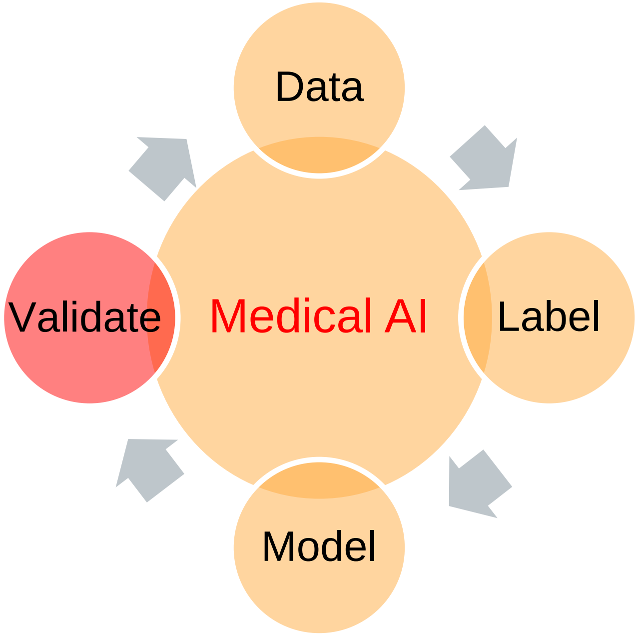
RUNTIME COMPARISON ON THE ROI (SIZE 2800 × 2800) (UNIT: MINUTE)

Network	Methods	stride 32	stride 16
Fast ScanNet	ours	**0.0182**	**0.0200**
ScanNet [48]	ours	**0.0182**	0.0730
GoogleNet	HMS and MIT	0.6683	2.6734
ResNet-34	EXB Research co.	0.7240	2.8962
AlexNet	NLP LOGIX co.	0.3342	1.3367
VGG16(patch-based)	-	0.9747	3.8987

100x faster

[JAMA 2017, WACV 2018, TMI 2019]

Outline



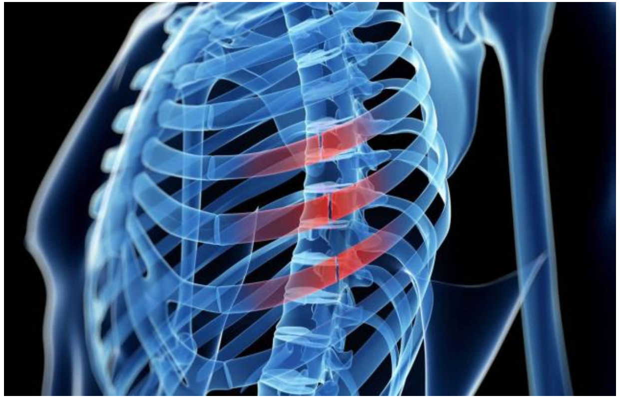
Key Challenges:

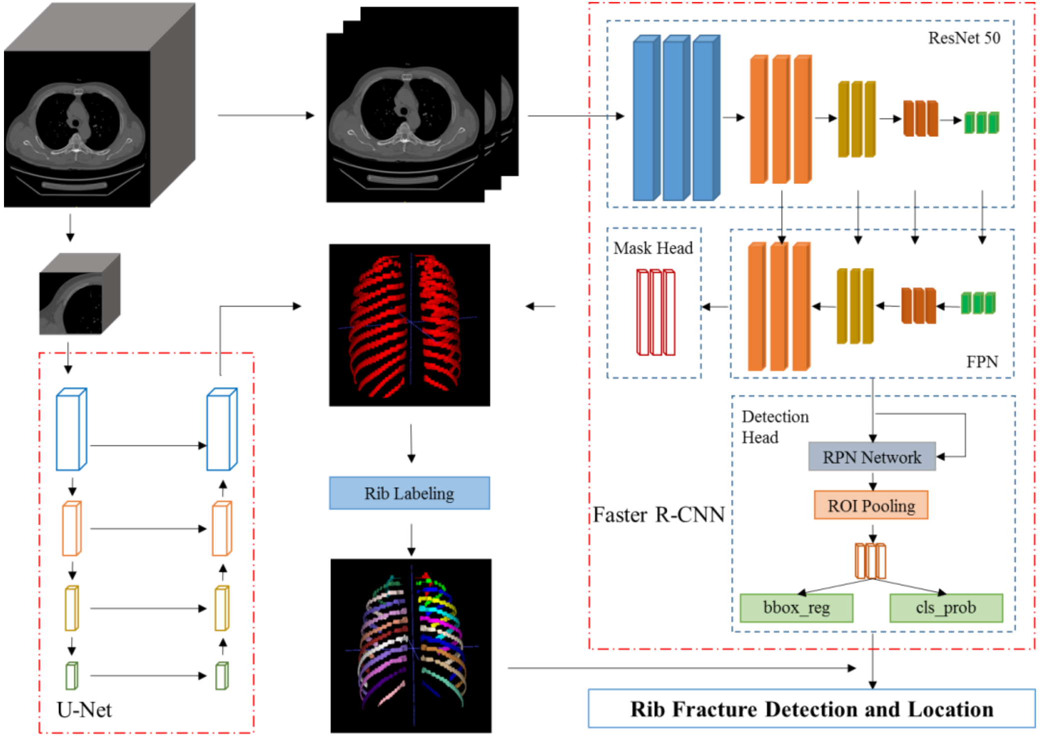
Human-machine collaboration

- Fracture Detection,
- Tumor Segmentation.

Rib Fracture Detection from Multi-center Thoracic CT Images

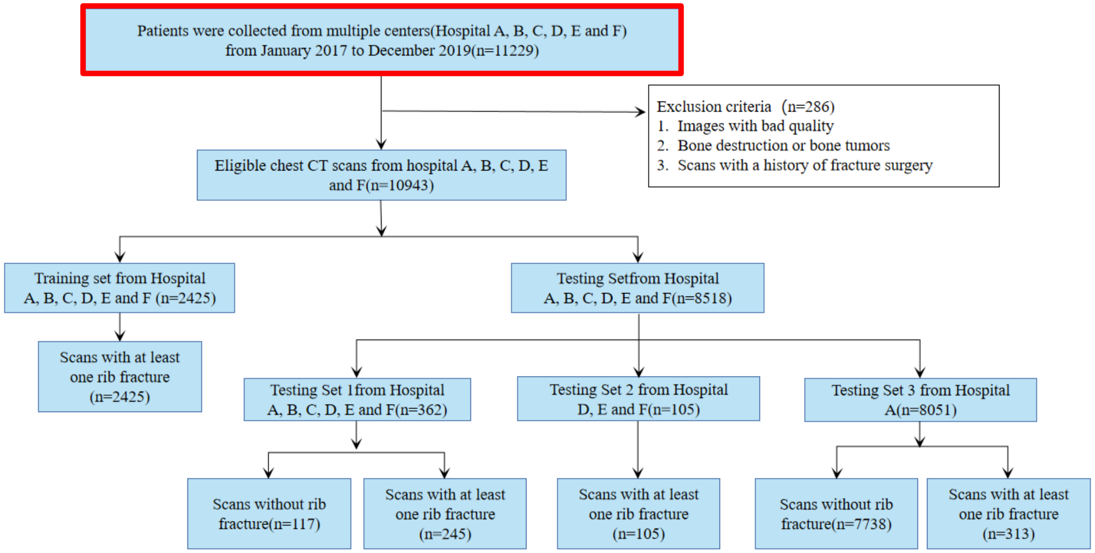
Problem and Development

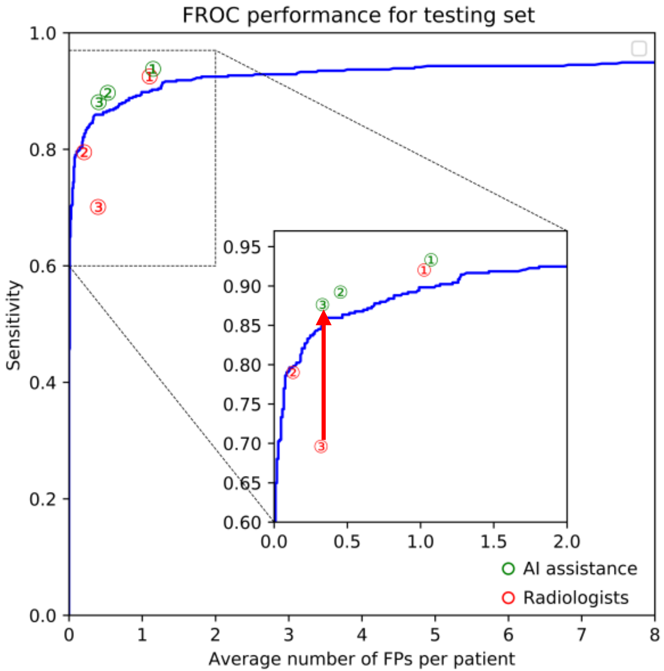




Rib Fracture Detection from Multi-center Thoracic CT Images

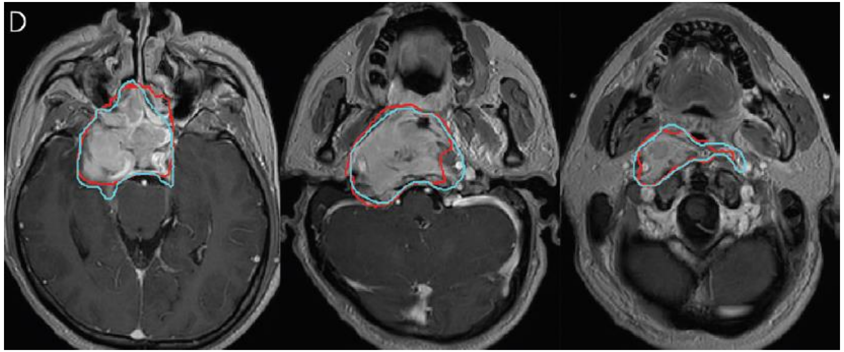
Dataset and Results



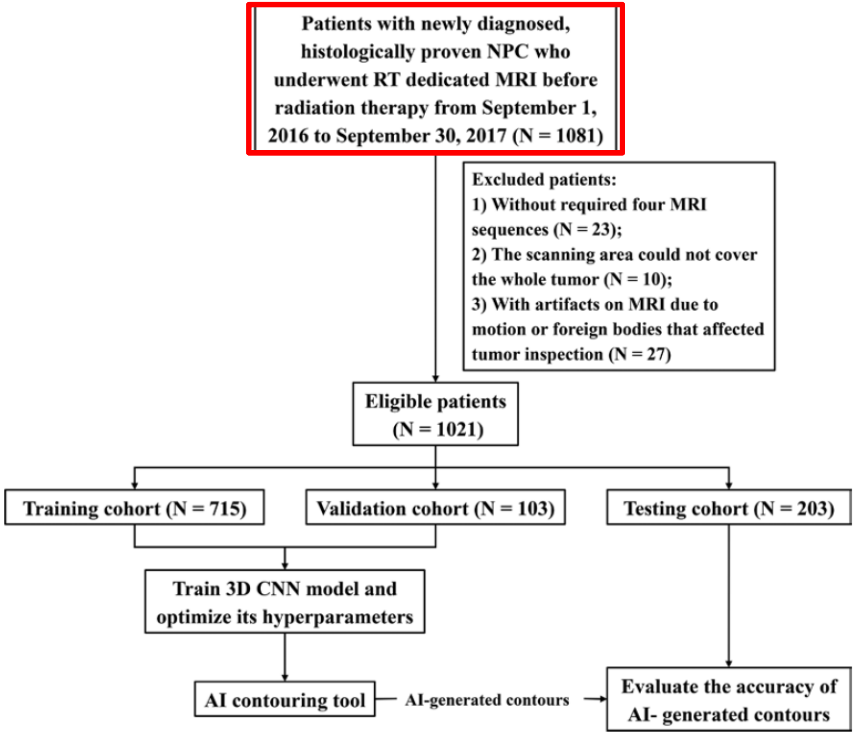


Automated Contouring of PTV for Nasopharyngeal Carcinoma from MRI

Problem and Dataset



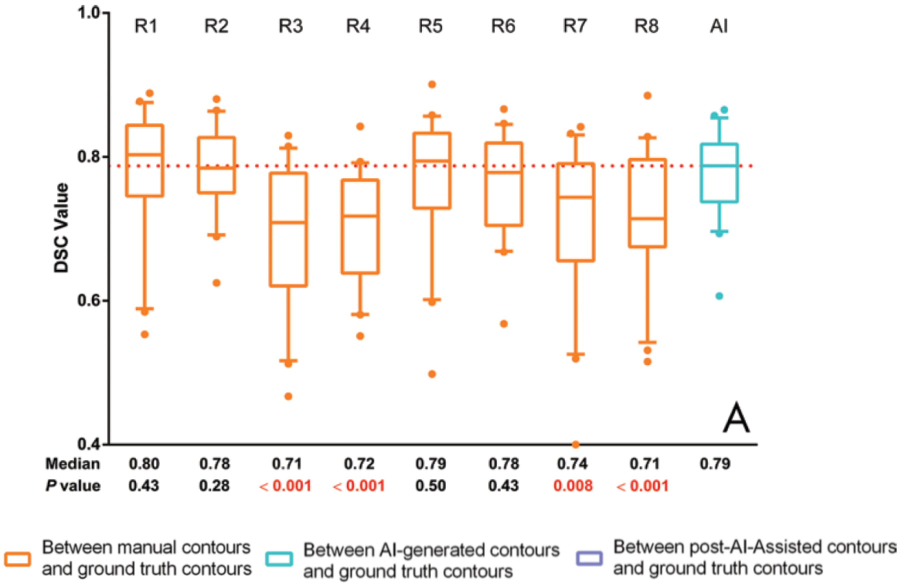
Blue and red lines indicate human experts and AI, respectively.

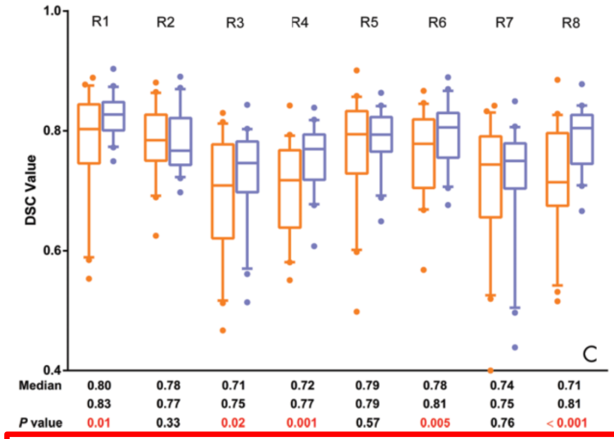


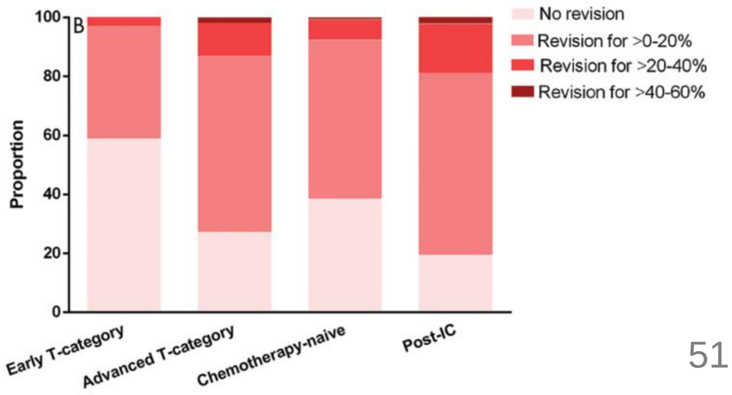
[Li, Chen, Sun, et al. Radiology 2019]

Automated Contouring of PTV for Nasopharyngeal Carcinoma from MRI

Results





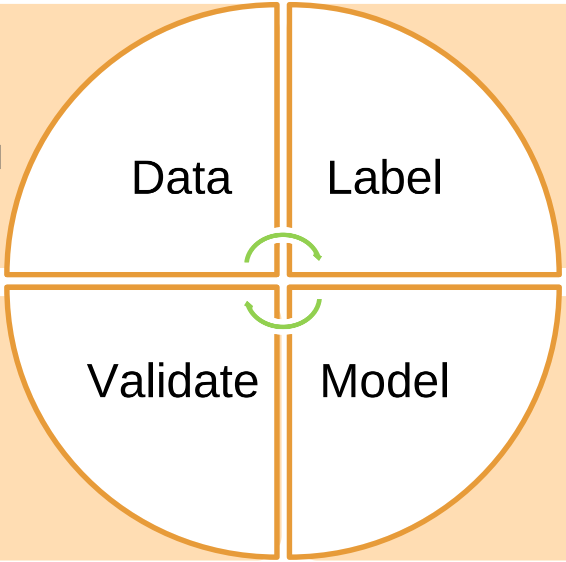


[Li, Chen, Sun, et al. Radiology 2019]

Summary

Limited data
[MICCAI'15,'16,JBHI'16, IEEE Cybernetics'17, , IJCAI'18, TMI'20]
Radiology

Embrace and harness imperfect labels
[MICCAI'19,Lancet Digital Health'19, MIA'20, JBHI'20]
Ophthalmology

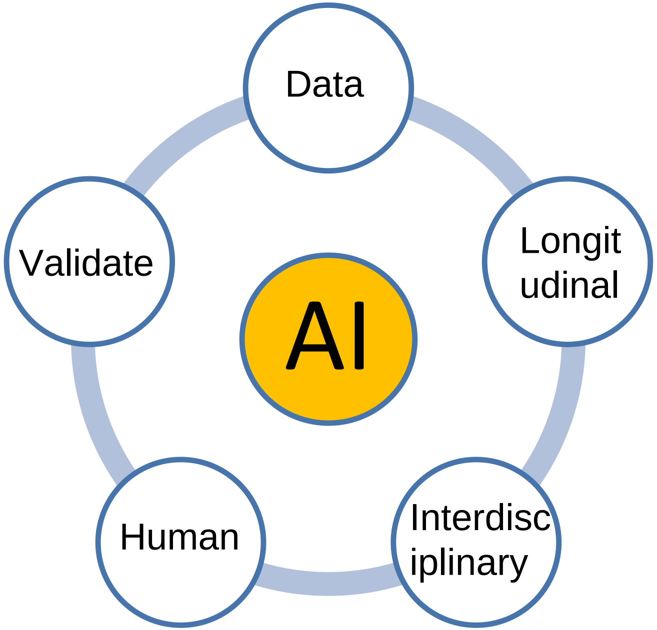


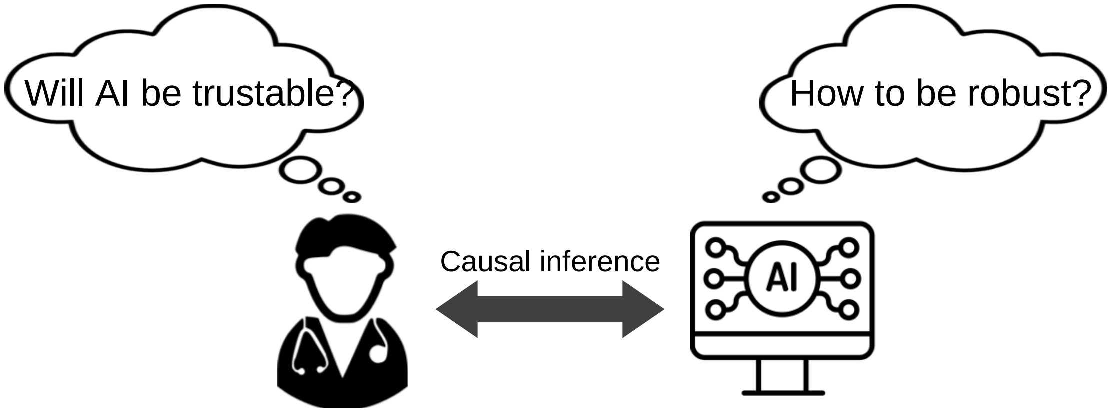
Human-machine collaboration
[Radiology'19, Lancet Digital Health'19, JAMA'17, et al.]
Radiology and Radiotherapy

Robust and scalable inference
[MICCAI'16,'17,AAAI'16, CVPR'16, MIA'17, JAMA'17, NeuroImage'18, TMI'18,'19]
Radiology and Pathology

Future Directions

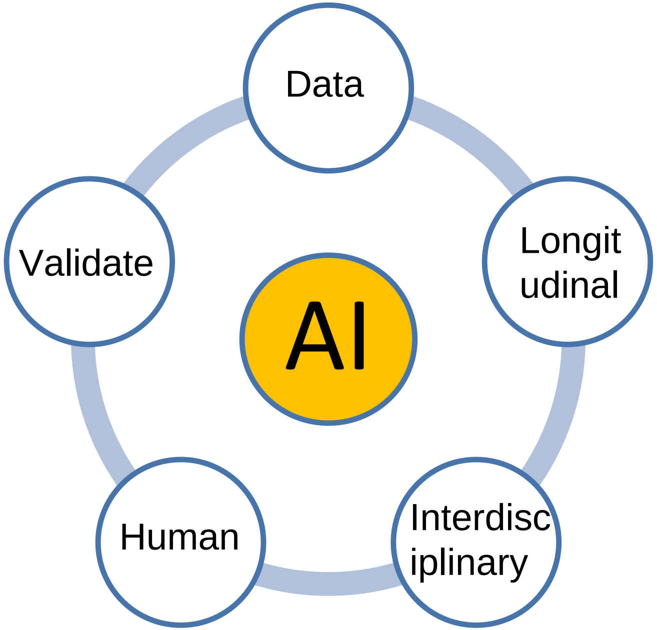
- Trustable, generalizable, and explainable AI algorithms.

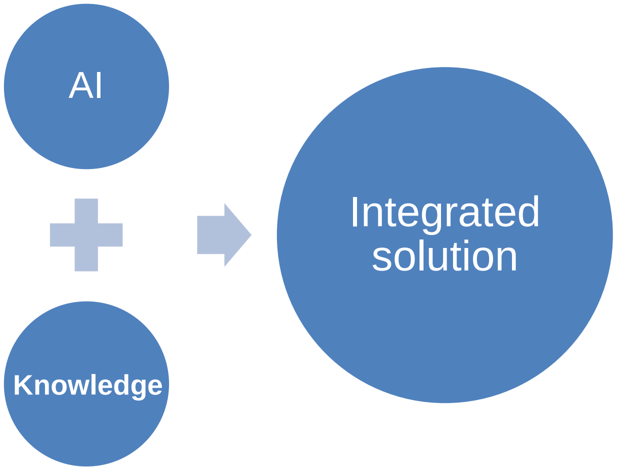




Future Directions

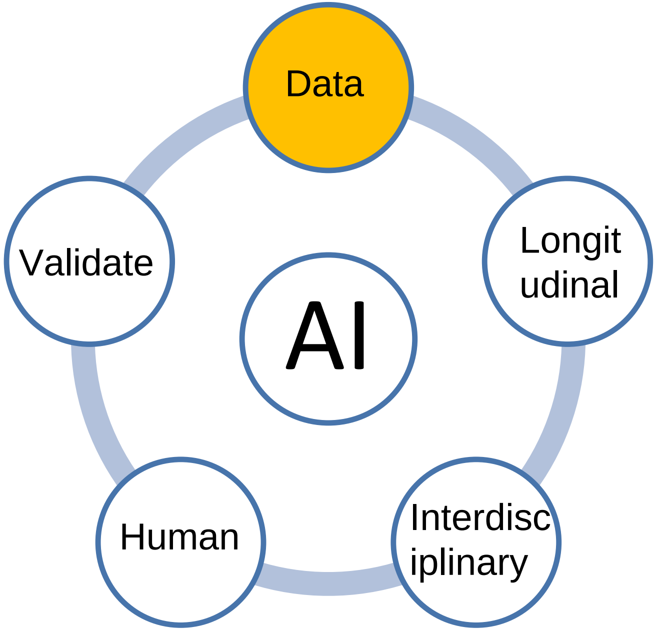
- Embedding medical knowledge (evidence discovery) into data-driven learning

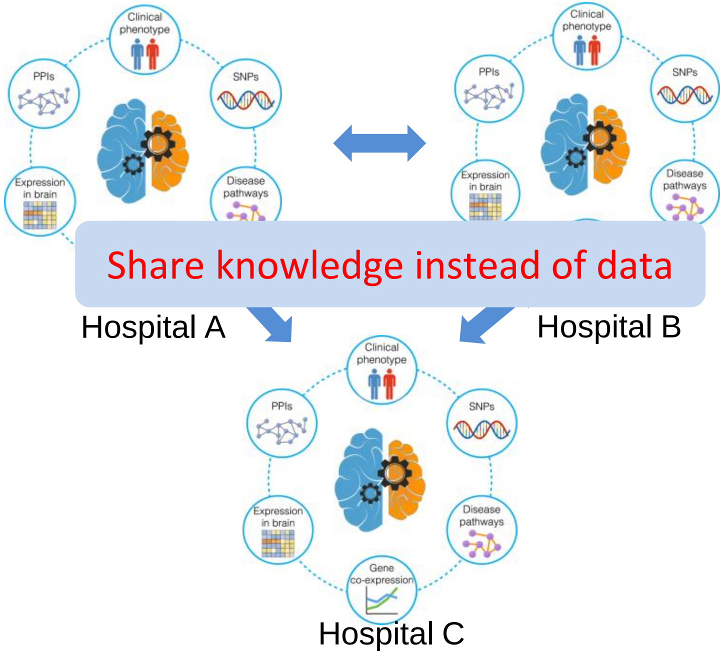




Future Directions

- AI for personalized precision medicine from image-only to patient-level with heterogeneous data modelling (e.g., genome, image, pathology, clinical data).

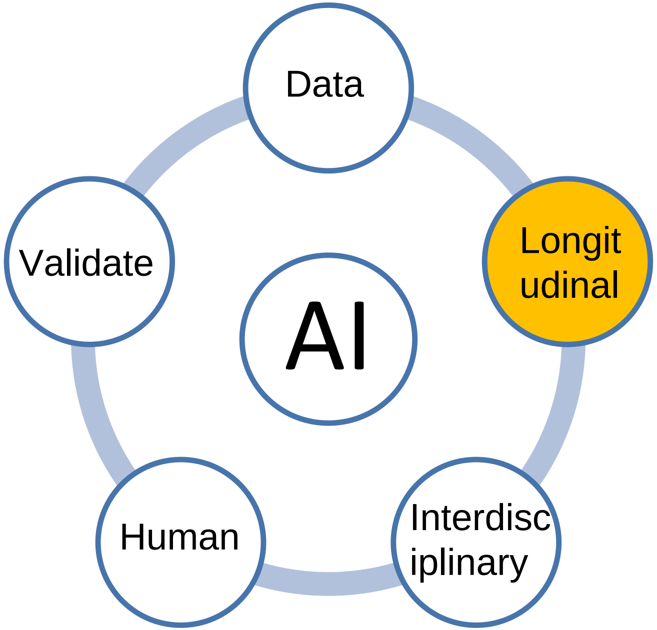


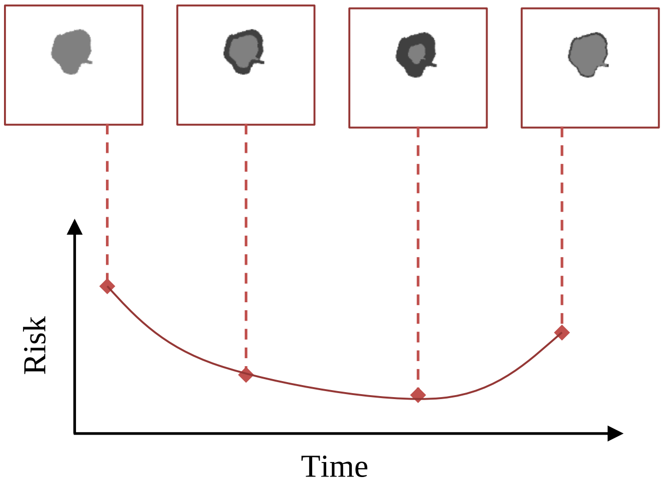


[Elena, et al. Nature Scientific Data]

Future Directions

- Full-stack AI solution in data acquisition, screening, diagnosis, progression, treatment, and prognosis (e.g., molecular underpinning and survival analysis).

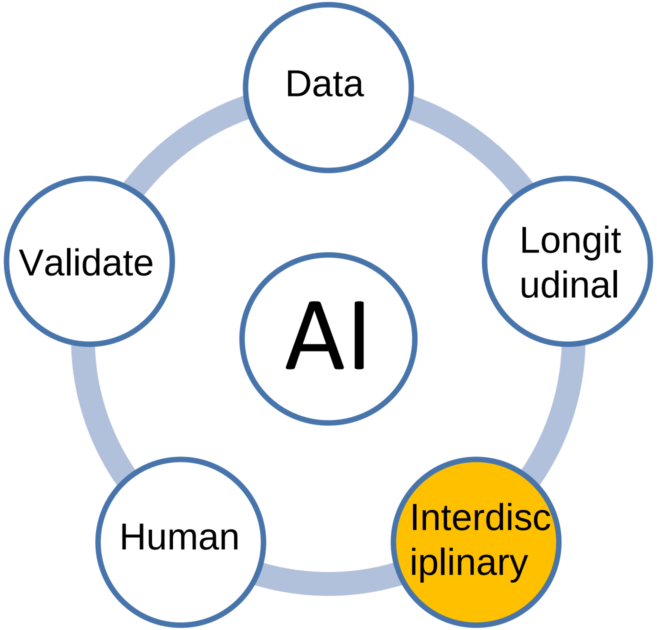


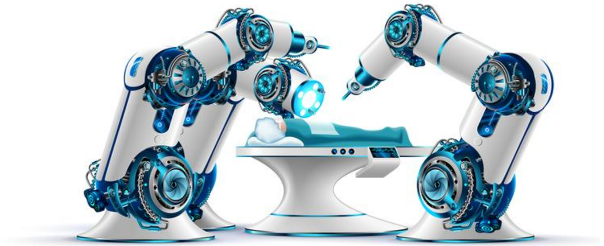


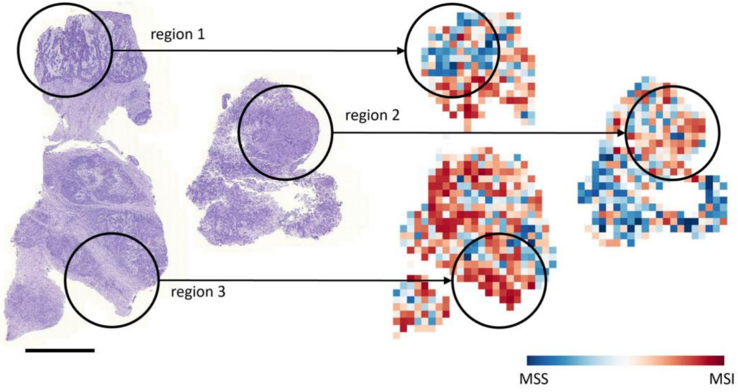
[Hosny, et al. Nature Reviews Cancer]

Future Directions

- Interdisciplinary research between AI and other domains, such as surgical robotics, drug discovery, image-guided therapy, etc.



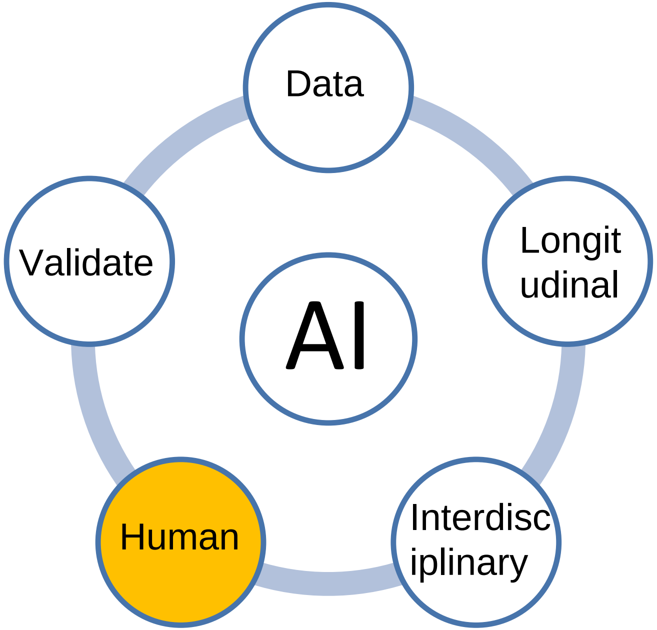


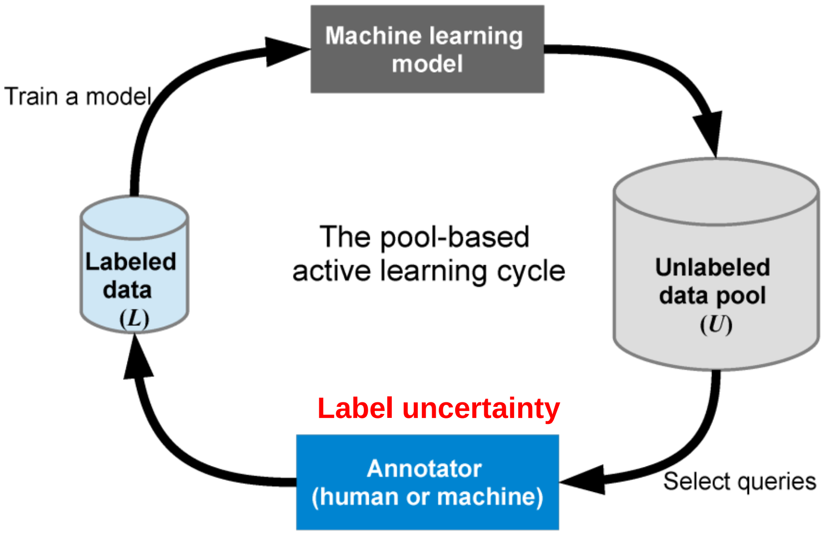


[Kather, et al. Nature Medicine]

Future Directions

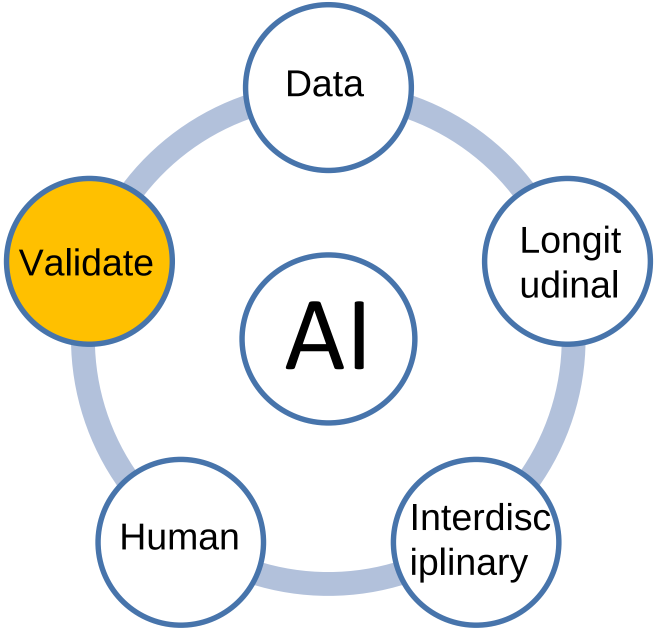
- Human-in-the-loop active learning, maximize data usage & minimize annotation efforts using annotation-efficient learning.





Future Directions

- Human-machine collaboration research with application to clinical translation and validation, etc.



https://medicalfuturist.com/

Take Home Messages

- AI for Medical Image Analysis has tremendous value in clinical practice.
- Versatile applications from image acquisition to disease diagnosis and prognosis.
- Core challenges still exist. Computational methods are important and collaboration with doctors is absolutely indispensable.
- Lots of fun stuff with models, graphics, understanding of disease mechanism and our body, etc.

THE DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING
計算機科學及工程學系

Thank you!

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Google scholar:

https://scholar.google.com.hk/citations?user=Z_t5DjwAAAAJ&hl=en