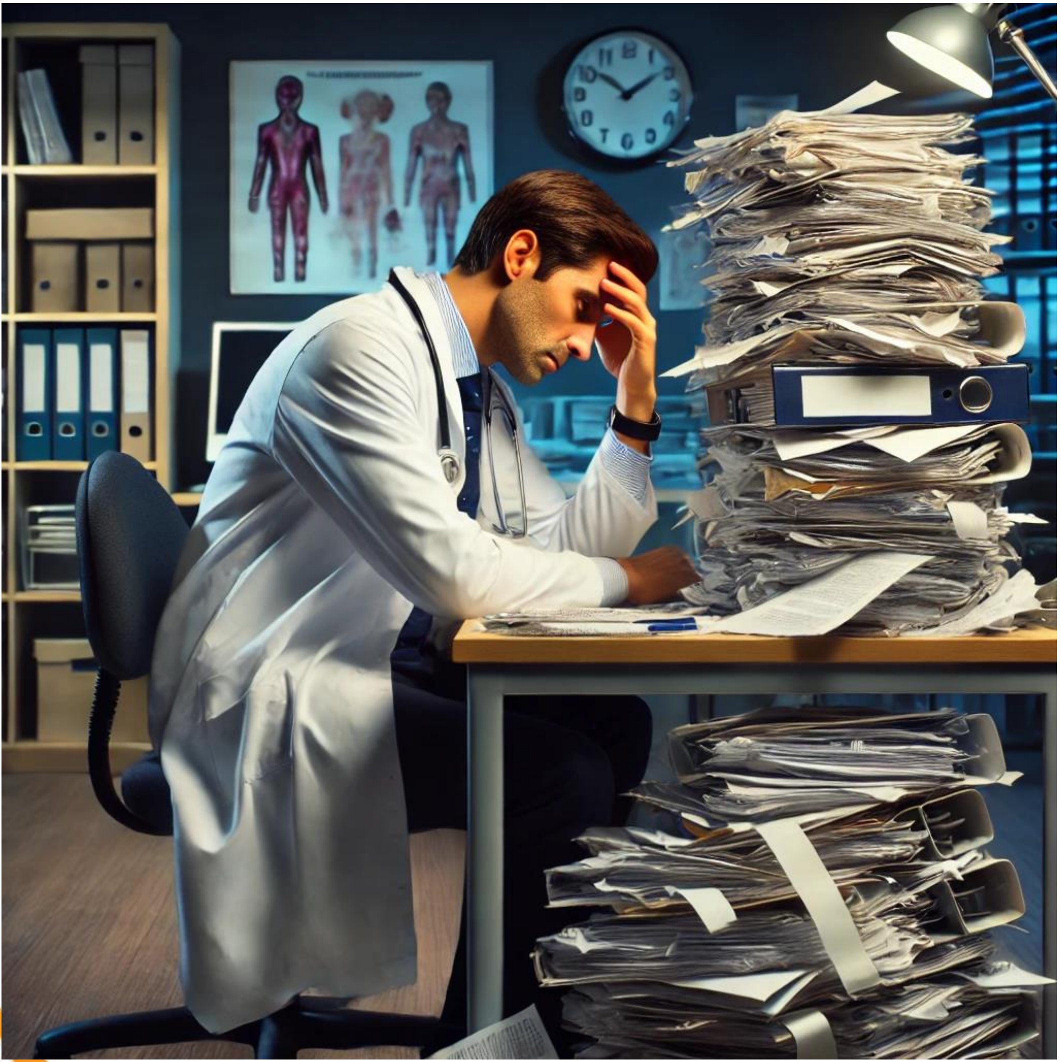
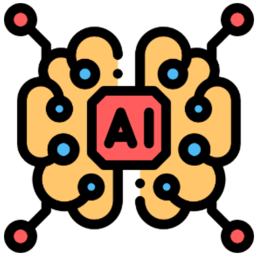
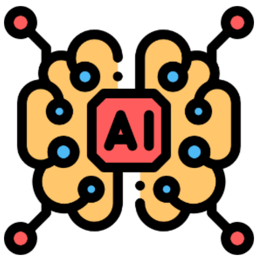
Artificial Intelligence (AI) in Disease Management in Thu Duc City

Trần Minh Triết
University of Science
Viet Nam National University Ho Chi Minh City

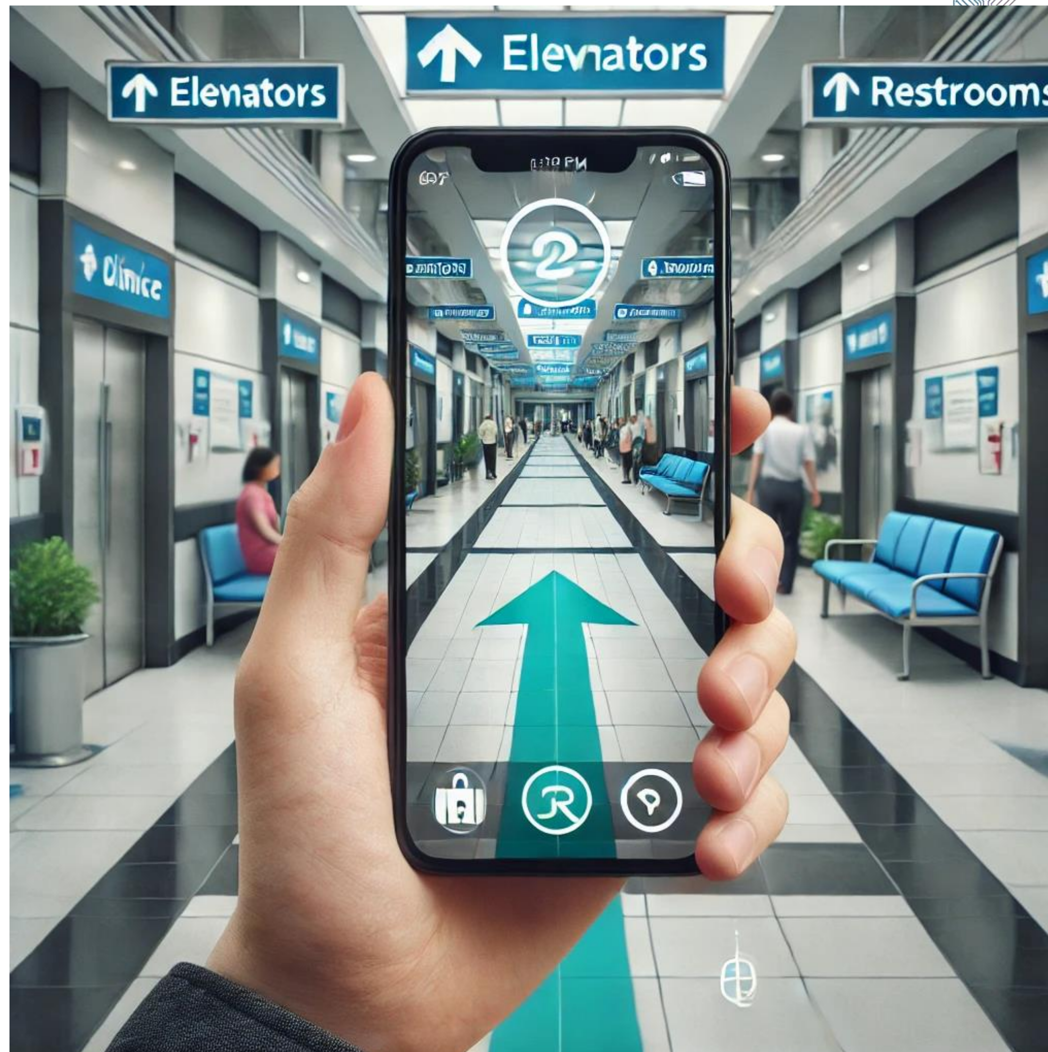


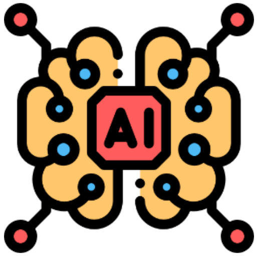

AI


HCI
IC

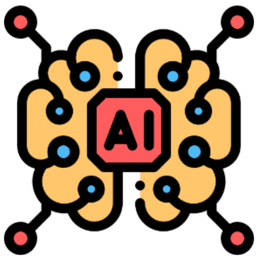

AI


HCI
IC

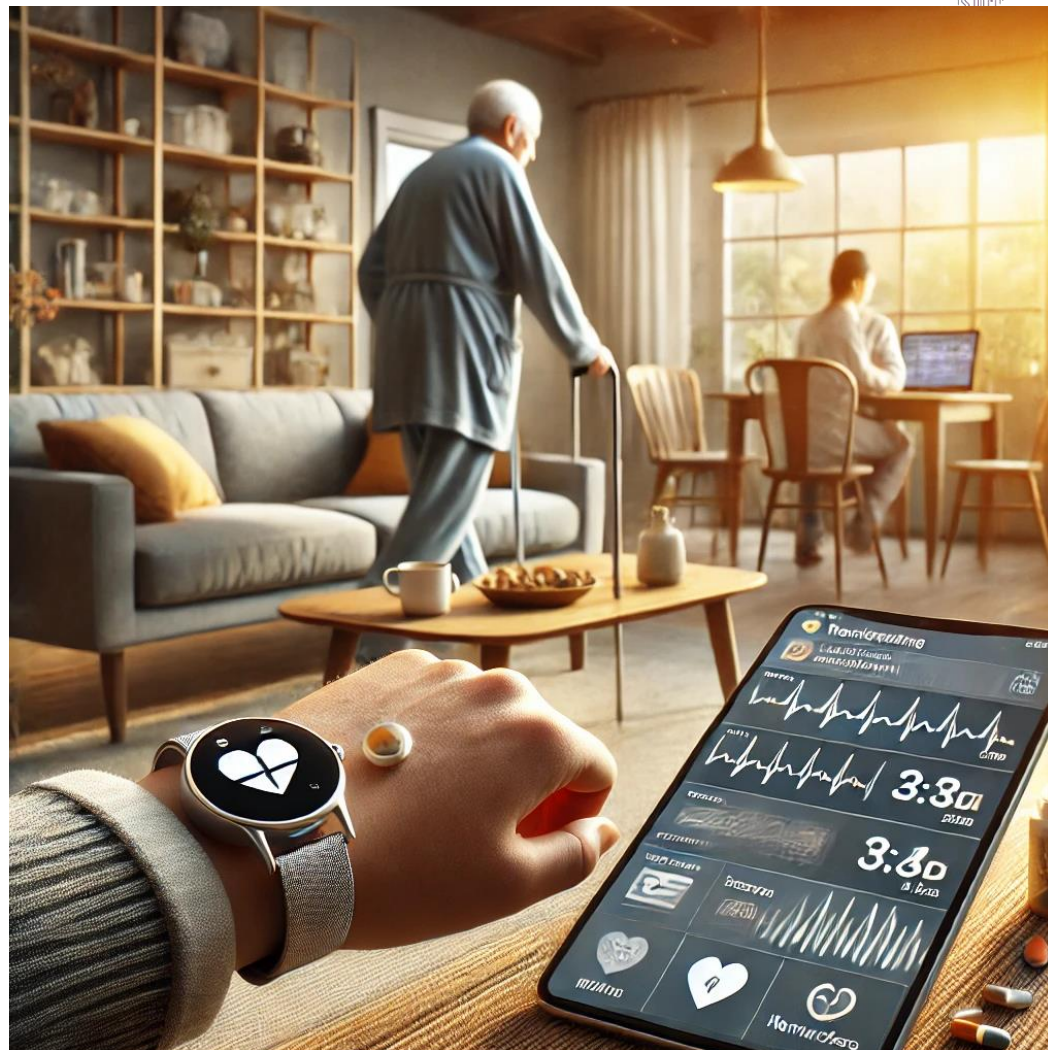

Elenators
Elevnators
Restrooms


AI


HCI
IC

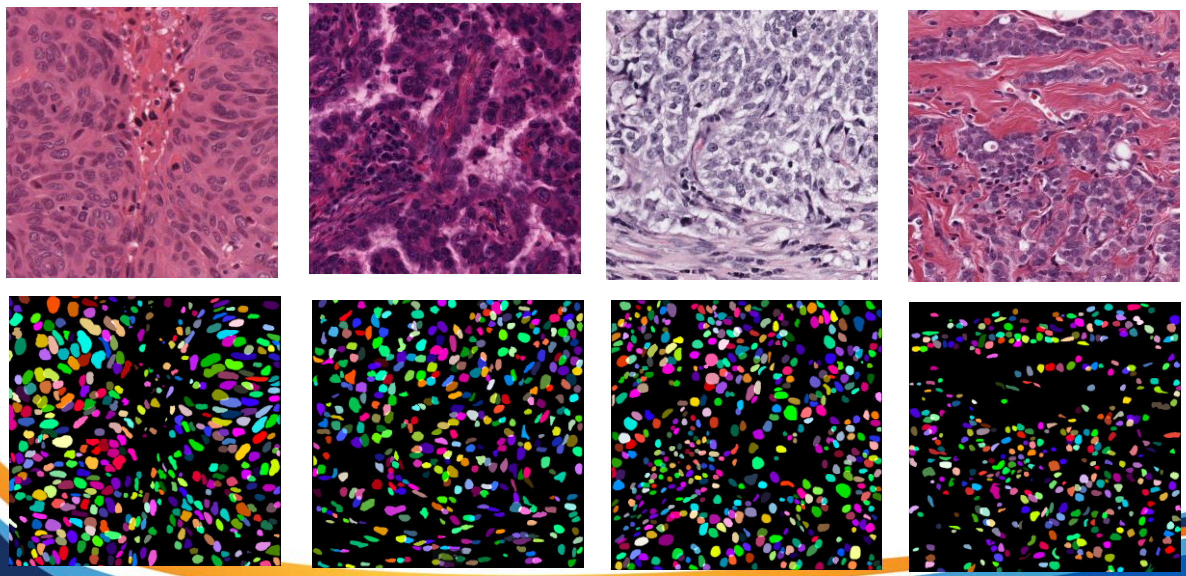



HCI



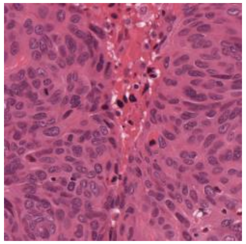
The story begins…

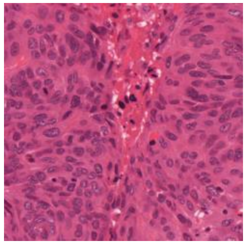
MoNuSeg: an official satellite event of MICCAI 2018
showcase the best nuclei segmentation techniques that will work on a diverse set of H&E stained histology images obtained from different hospitals spanning multiple patients and organs.



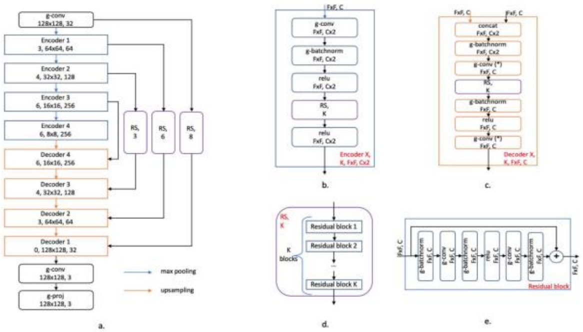
The story begins…

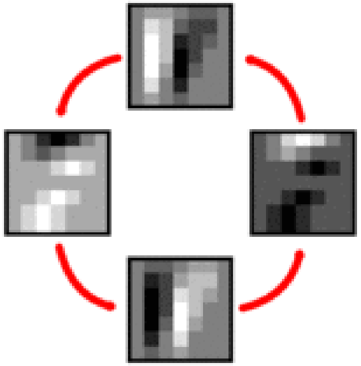
- Synthesize more data
- Modified U-Net
- Group-equivariant convolution





Original image New synthetic image

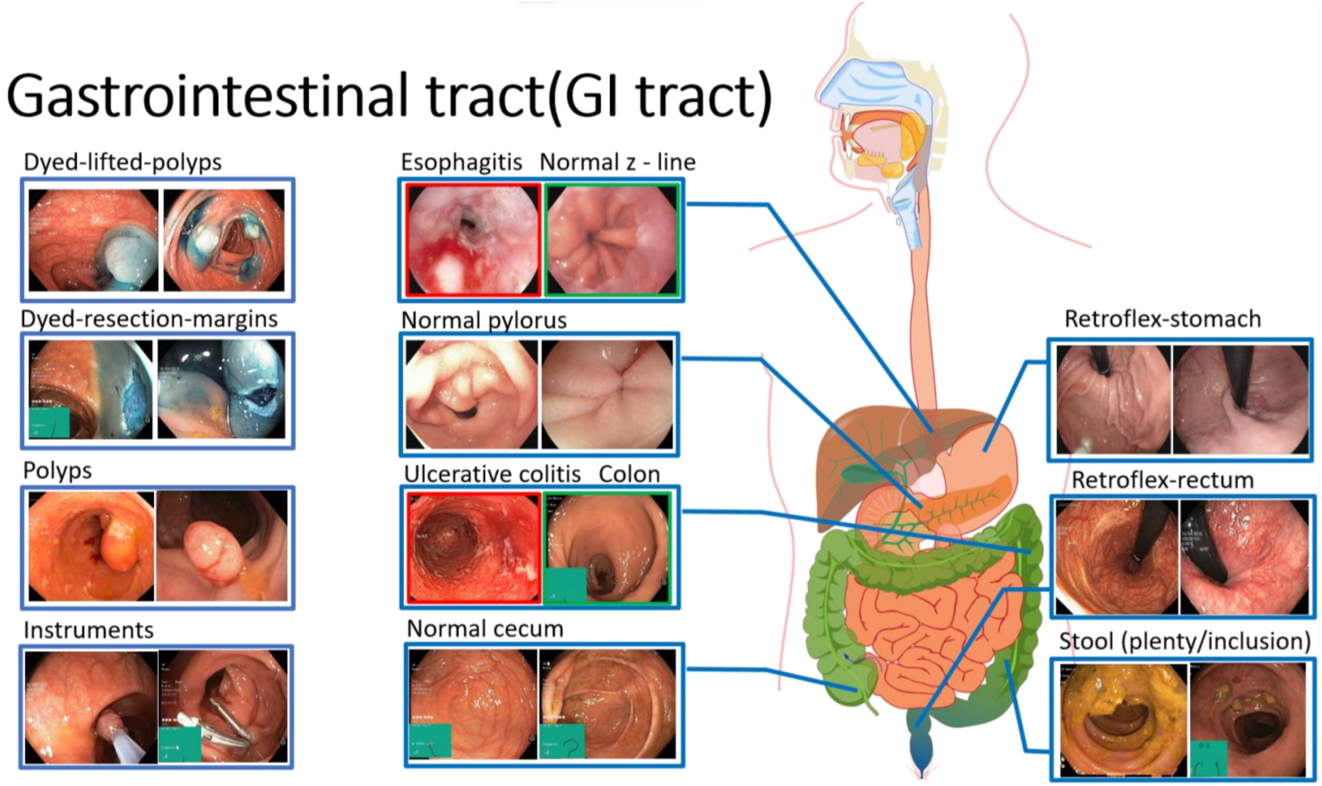




Benjamin Chidester *et.al*, **Enhanced Rotation-Equivariant U-Net for Nuclear Segmentation**, **CVPR Workshop** (2019)

A Multi-Organ Nucleus Segmentation Challenge, **IEEE Transaction on Medical Imaging** 39(5): 1380-1391 (2020)

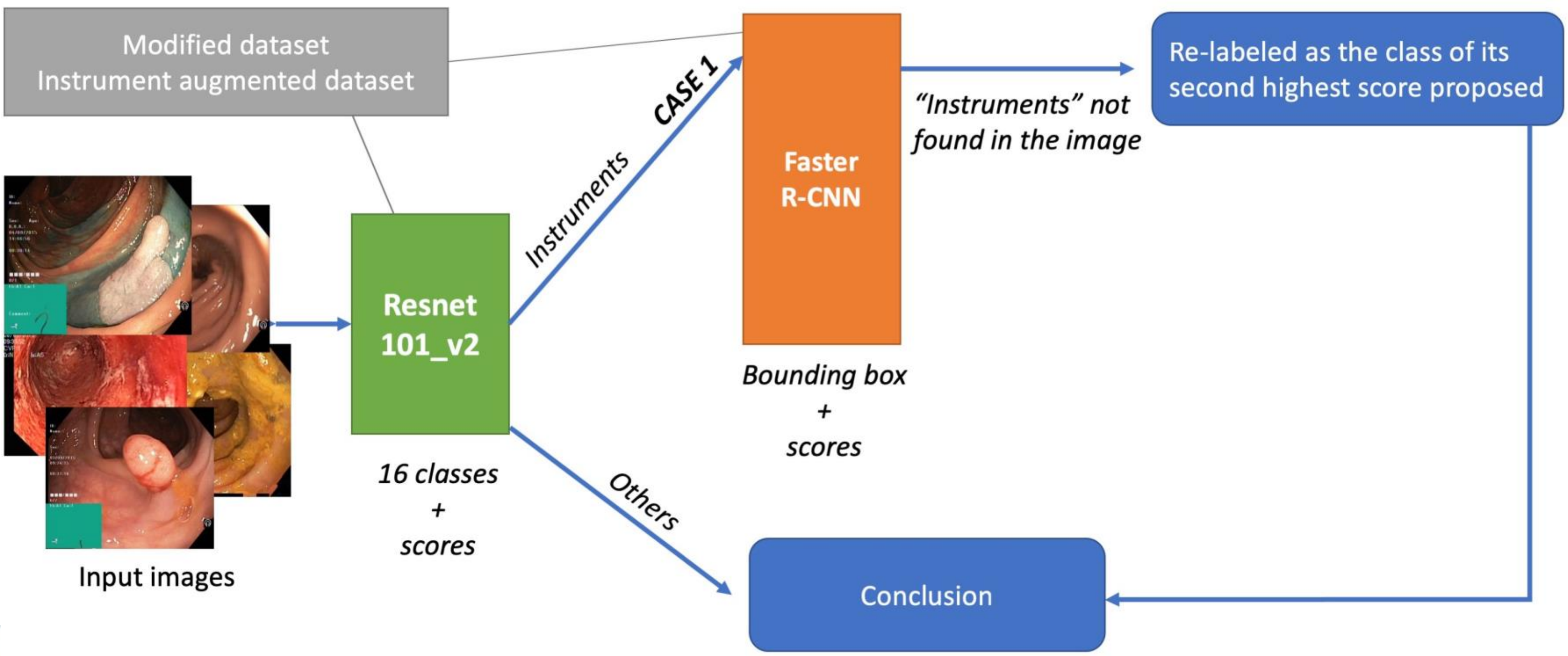
Another story…



Trung-Hieu Hoang *et.al*, **An Application of Residual Network and Faster - RCNN for Medico: Multimedia Task at MediaEval 2018**. **MediaEval (**2018)

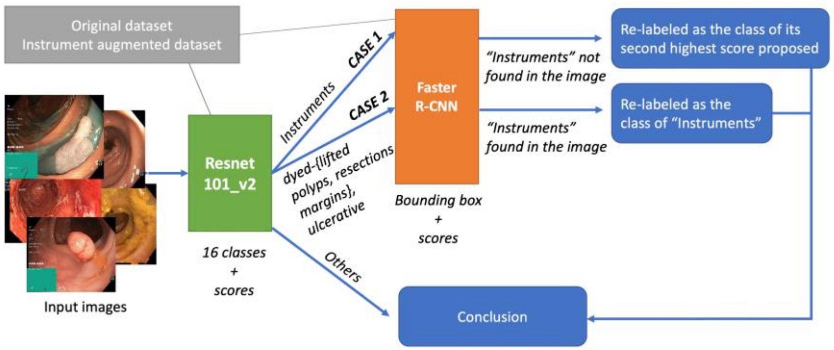
A comprehensive analysis of classification methods in gastrointestinal endoscopy imaging. **Medical Image Analysis** 70: 102007 (2021)

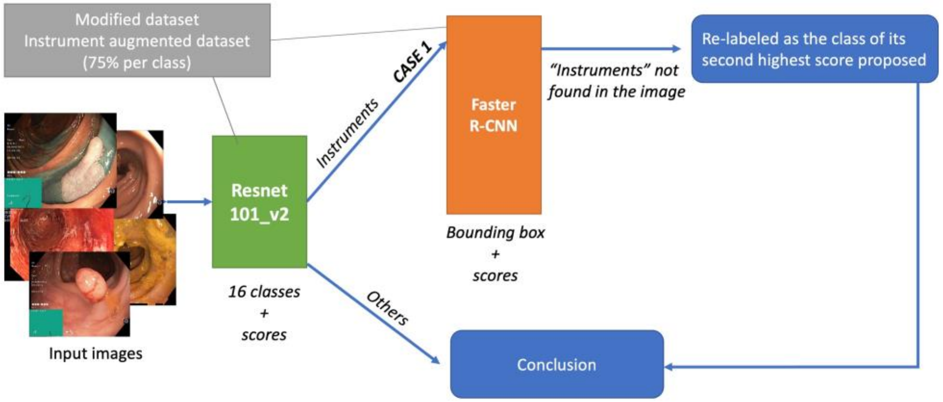
Approach

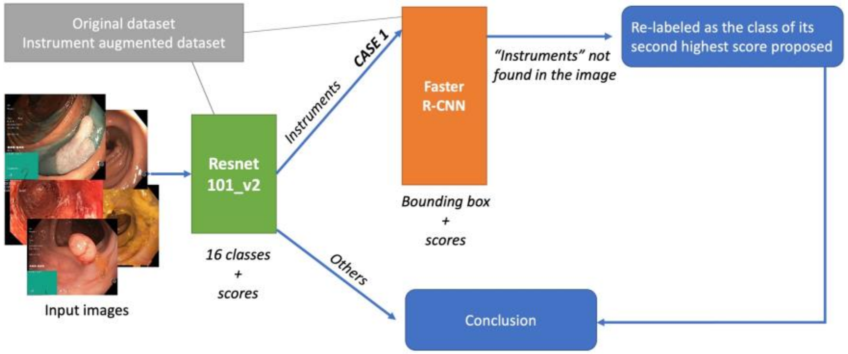


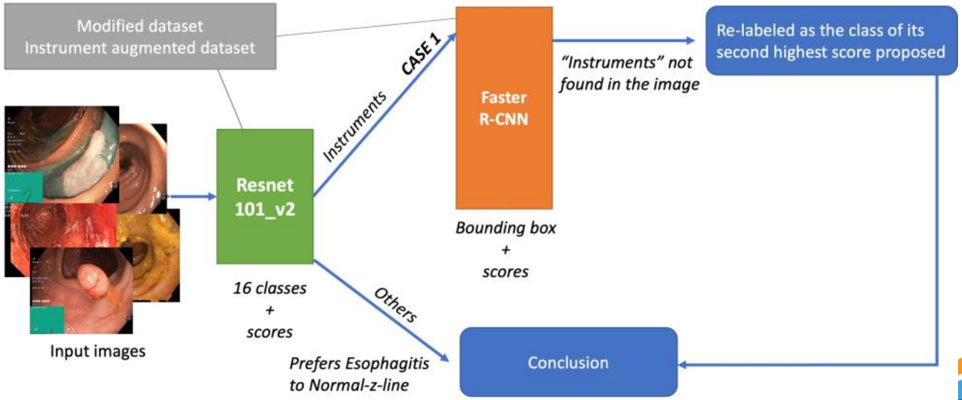
Modified dataset
Instrument augmented dataset
Input images
Resnet 101_v2
16 classes + scores
Instruments
CASE 1
Others
Faster R-CNN
Bounding box + scores
"Instruments" not found in the image
Re-labeled as the class of its second highest score proposed
Conclusion

Approach



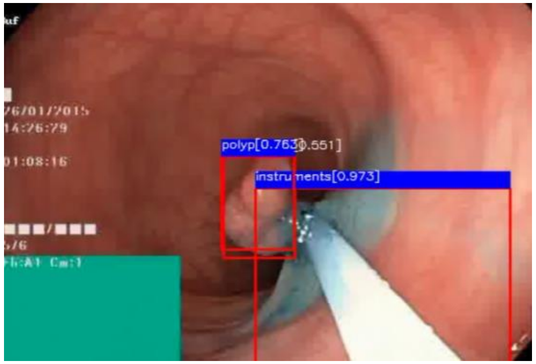






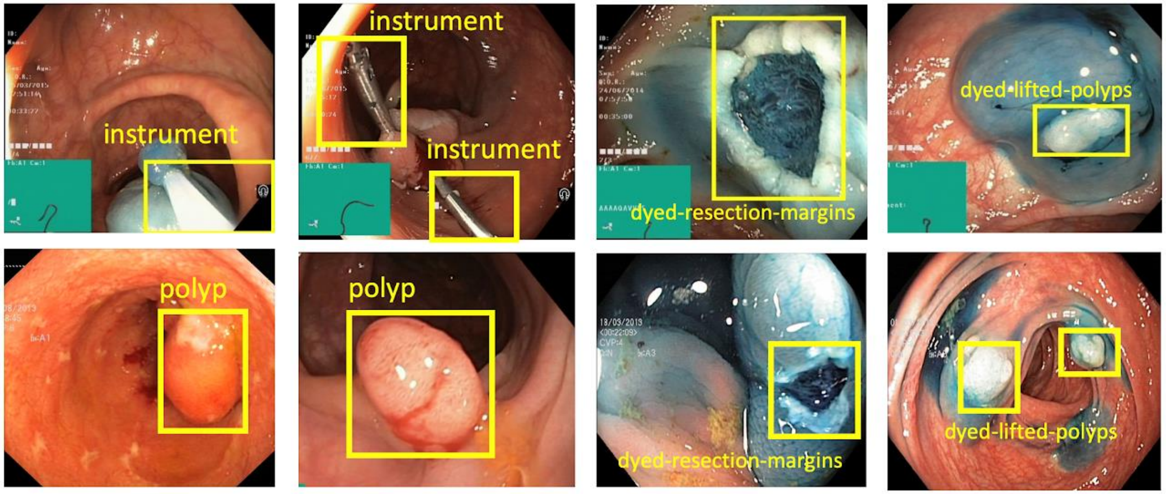
Other configurations

Another story…



https://endoscopy.selab.hcmus.edu.vn/

Bounding boxes pf *dyed-lifted-polyps, dyed-resection-margins, instruments, polyp*:
KVASIR dataset (v2)
Dev. dataset of Biomedia ACM MM Grand Challenge 2019



Trung-Hieu Hoang *et.al*, **Enhancing Endoscopic Image Classification with Symptom Localization and Data Augmentation**. **ACM Multimedia** : 2578-2582 (2019)

CCBANET: Cascading Context and Balancing Attention for Polyp Segmentation

Tan-Cong Nguyen, Tien-Phat Nguyen, Gia-Han Diep, *et.al*

CCBANet: Cascading Context and Balancing Attention for Polyp Segmentation. MICCAI (1) 2021: 633-643

In memory of Gia-Han Diep

Polyp Segmentation Problem

- **Colorectal Cancer**: one of the most common causes of human mortality in the world: 9.4% of worldwide cancer deaths, nearly 1 million cases in 2020.
- Detection systems can save doctors time and help automatic polyp segmentation to detect all types of polyps
- Challenges: Medico, EndoCV2021
- Datasets: Kvasir-SEG, CVC-ClinicDB and CVC-EndoSceneStill
- Studies: U-net, U-net ++, ResUNet, ResUNet++, U2-Net, PraNet, ACSNet

13

Polyp Segmentation Problem

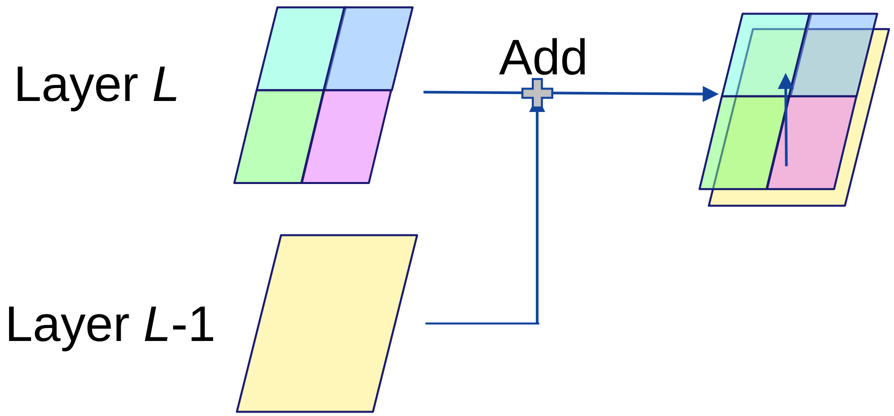
Input

Output

Need a segmentation method for both accuracy and efficiency

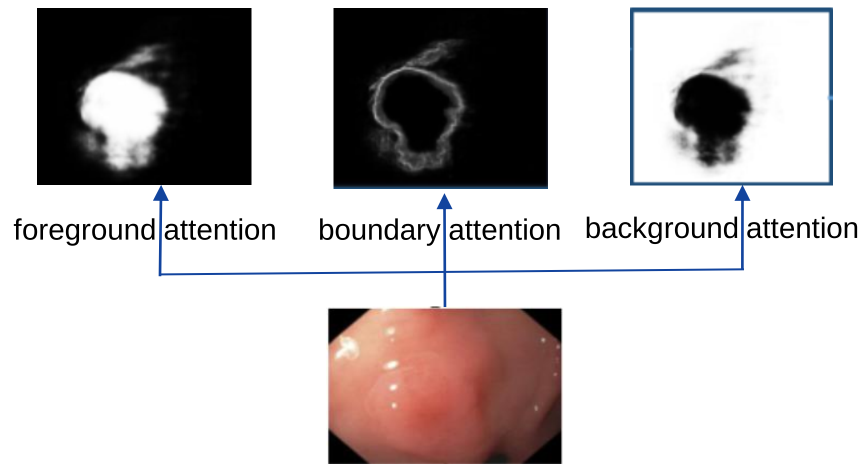
Key Ideas

Cascading context information



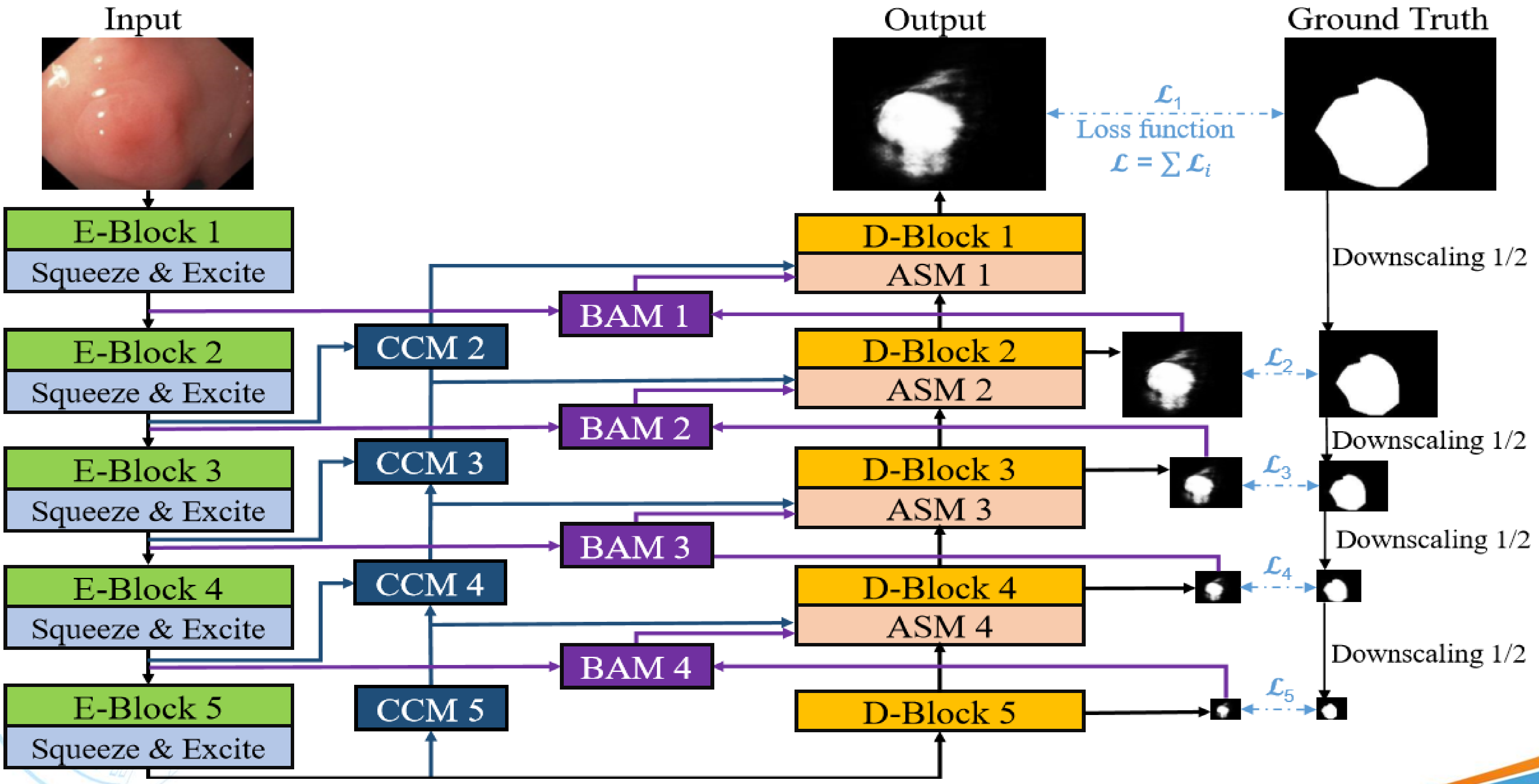
Combine regional and global contextual information for each layer

Balancing attention for:

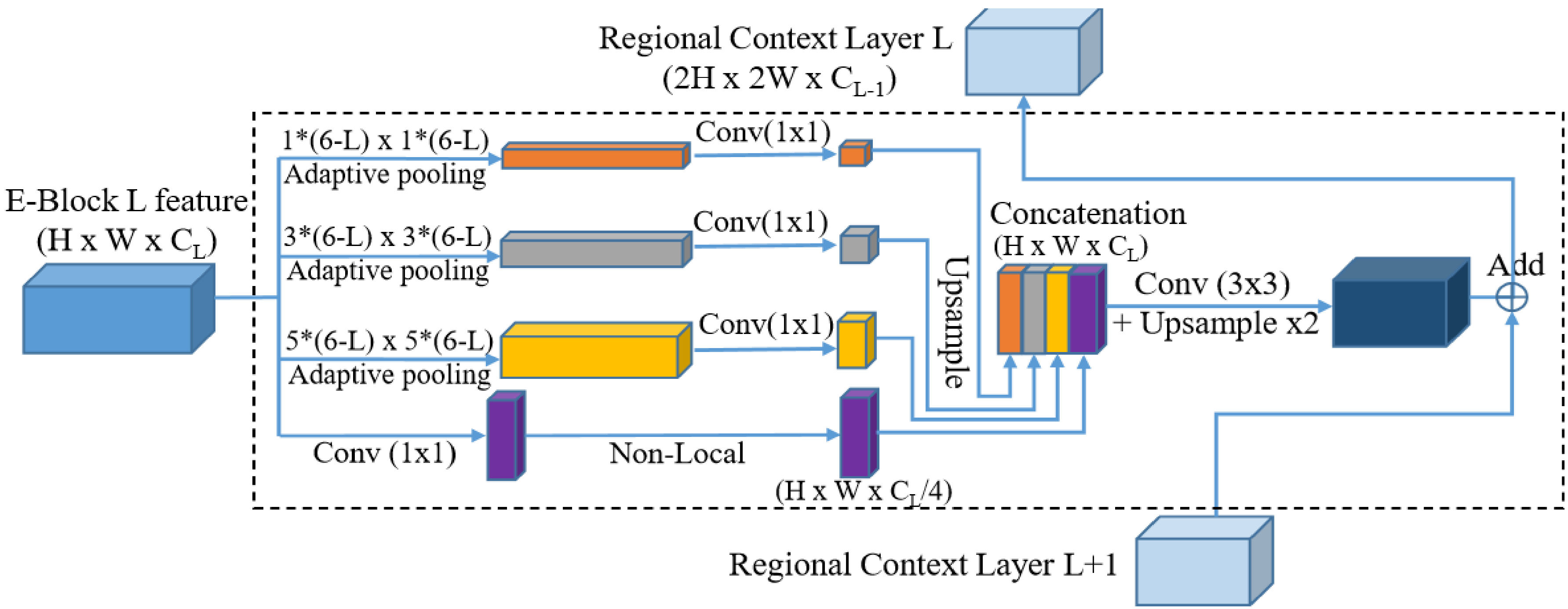


implements the attention mechanism for the three regions separately

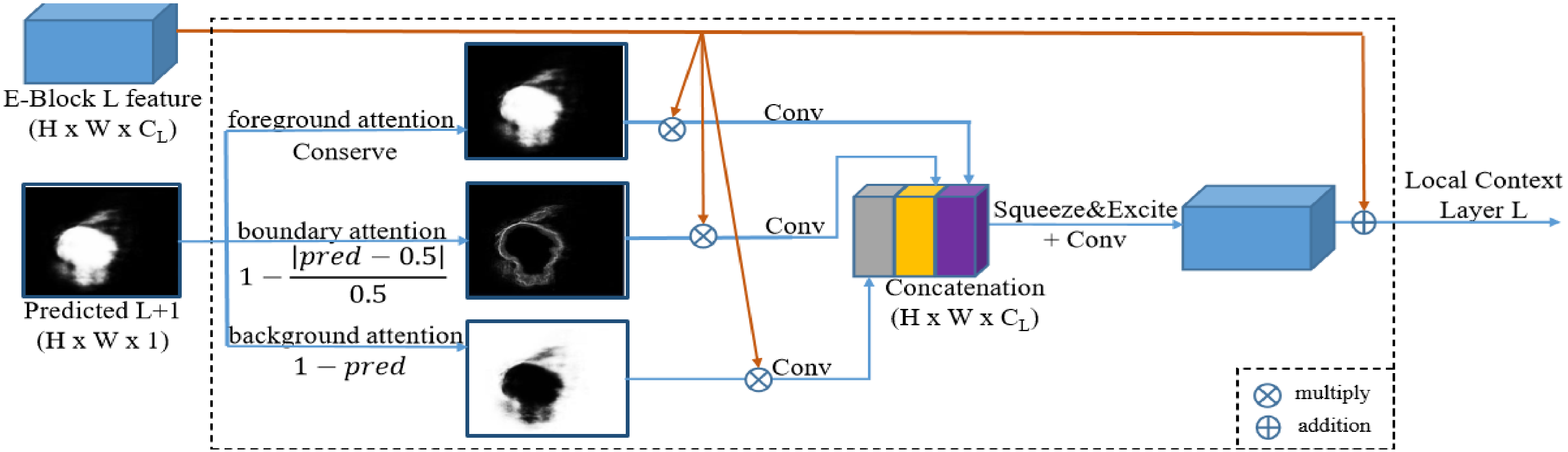
Overview of the CCBANet model



Cascading Context Module (CCM)



Balancing Attention Module (BAM)



Experiment Result on Kvasir-SEG

Method	Dice↑	IoU (Jaccard)↑	Recall↑	Precision↑	Accuracy↑	F2↑
U-Net	79.94	69.35	81.51	82.91	82.17	81.79
U-Net’	84.57	77.21	88.09	86.49	88.78	85.00
U-Net++	88.10	81.68	91.09	89.30	91.82	90.73
Residual U-Net	72.50	59.84	72.42	79.35	73.12	73.71
ResUnet++	83.48	75.74	87.69	83.67	88.40	86.86
PraNet	89.84	83.81	*92.14*	91.12	96.53	*91.93*
ACSNet	*91.38*	*84.12*	90.05	*92.74*	*97.04*	90.58
U2-Net	86.88	76.80	84.02	89.94	95.58	85.14
CCBANet (Our)	**92.59**	**86.21**	**92.21**	**92.98**	**97.43**	**92.36**

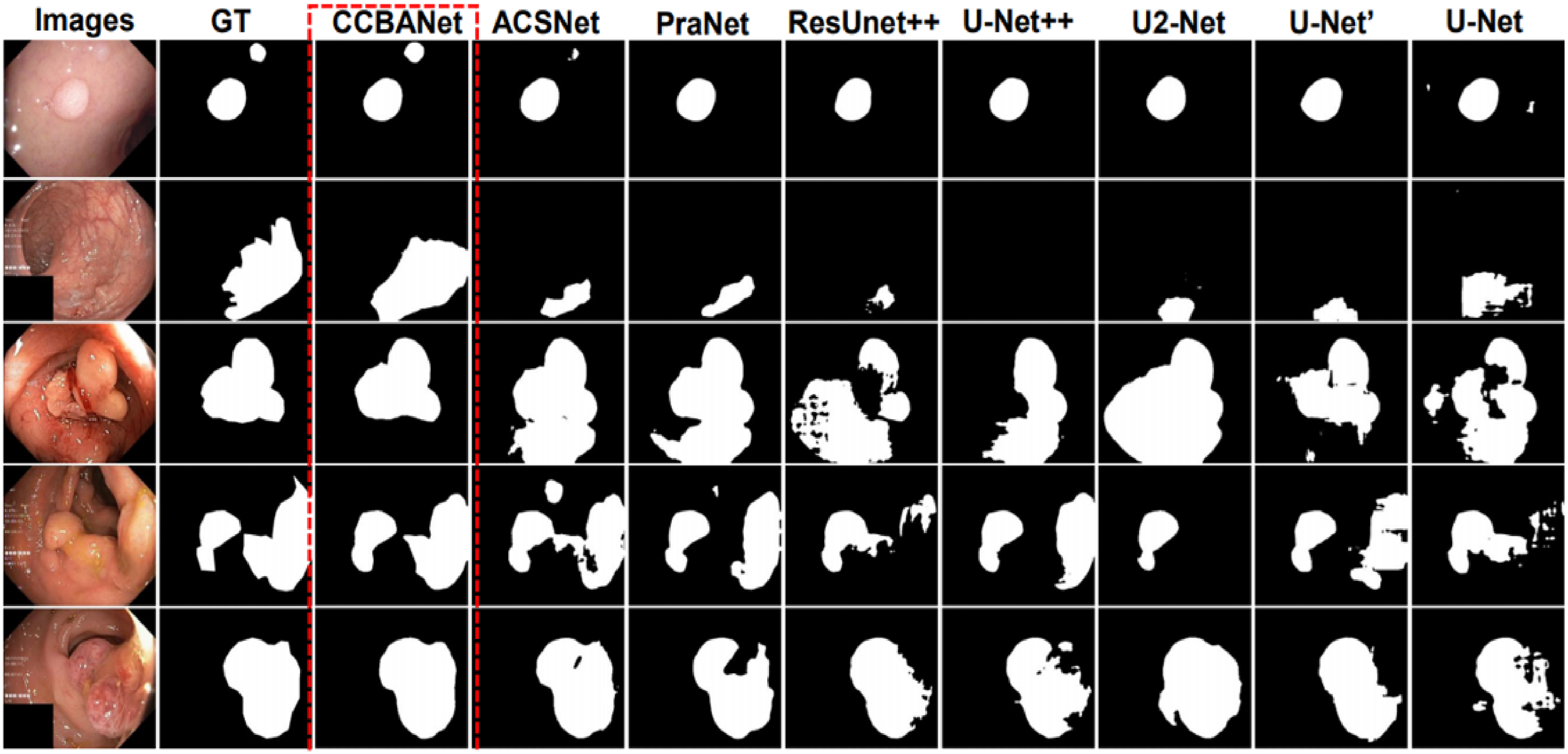
Experiment Result on CVC-ClinicDB (CVC-612)

Method	Dice↑	IoU (Jaccard)↑	Recall↑	Precision↑	Accuracy↑	F2↑
U-Net	87.62	79.47	87.32	89.99	87.36	87.84
U-Net	90.38	83.94	90.46	91.45	90.49	90.28
U-Net++	88.77	81.35	89.08	90.39	89.13	89.34
Residual U-Net	86.73	78.17	87.44	88.20	87.48	87.59
ResUnet++	87.93	81.06	88.23	90.40	88.30	88.66
PraNet	*94.59*	*90.26*	**95.00**	94.50	**99.23**	*94.90*
ACSNet	94.27	89.15	92.86	95.72	99.03	93.42
U2-Net	92.88	86.70	89.65	**96.34**	98.82	90.91
CCBANet (Our)	**95.43**	**91.26**	*94.79*	*96.08*	*99.22*	**95.05**

Experiment Result on CVC-EndoSceneStill

Method	Dice↑	IoU (Jaccard)↑	Recall↑	Precision↑	Accuracy↑	F2↑
U-Net	65.87	54.08	76.75	69.39	76.75	75.16
U-Net'	75.53	67.20	84.90	76.02	84.91	78.06
U-Net++	75.51	67.57	*86.87*	74.14	86.88	*83.99*
Residual U-Net	59.98	47.26	68.60	65.80	68.60	68.02
ResUnet++	51.09	42.74	78.27	47.57	78.28	69.32
PraNet	83.62	**76.55**	**88.33**	87.18	96.60	**88.10**
ACSNet	*84.78*	73.58	79.37	90.97	*97.37*	81.45
U2-Net	62.42	45.37	46.97	*93.03*	94.77	52.13
CCBANet[4] (Our)	**85.79**	*75.12*	79.29	**93.45**	**97.57**	81.77

Qualitative Results of Methods on Kavasir-SEG



The inference speed of our model is 39 frames/s – suitable for real-time prediction.

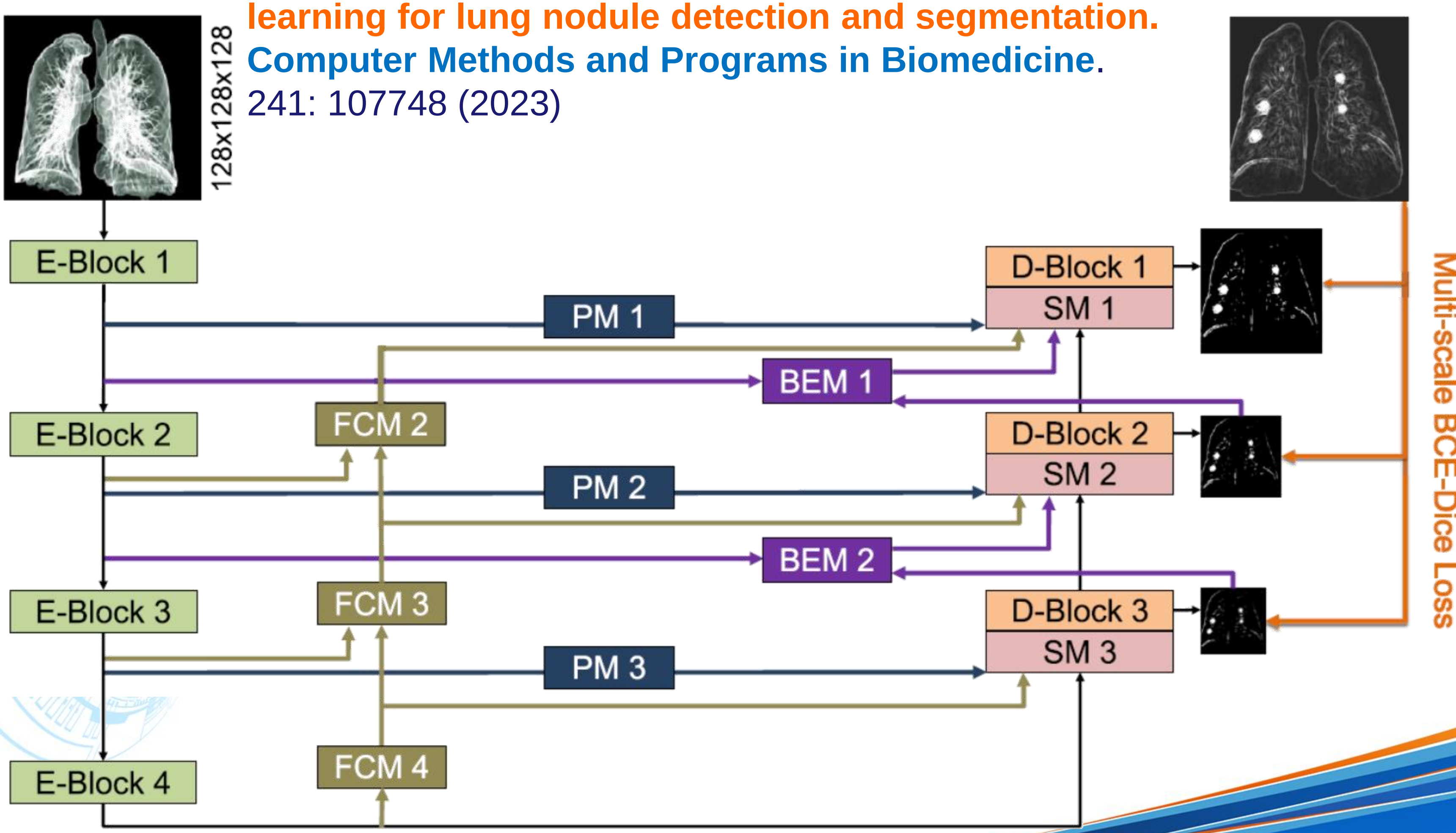
Ablation Study

Ablation study for CCBANet on the Kvasir-SEG dataset

Settings	Dice↑	IoU (Jaccard)↑	Recall↑	Precision↑	Accuracy↑	F2↑
Backbone	89.66	81.27	90.25	89.09	96.37	90.02
Backbone+CCM	91.64	84.56	90.09	93.23	97.13	90.70
Backbone+BAM(fg)	91.69	84.65	89.68	93.79	97.16	90.47
Backbone+BAM(bg)	92.15	85.44	90.52	93.84	97.31	91.17
Backbone+BAM(bo)	91.97	85.13	90.54	93.44	97.24	91.11
Backbone+BAM	92.31	85.71	92.52	92.09	97.31	92.43
Backbone+CCM+BAM	93.04	86.98	92.80	93.28	97.58	92.90

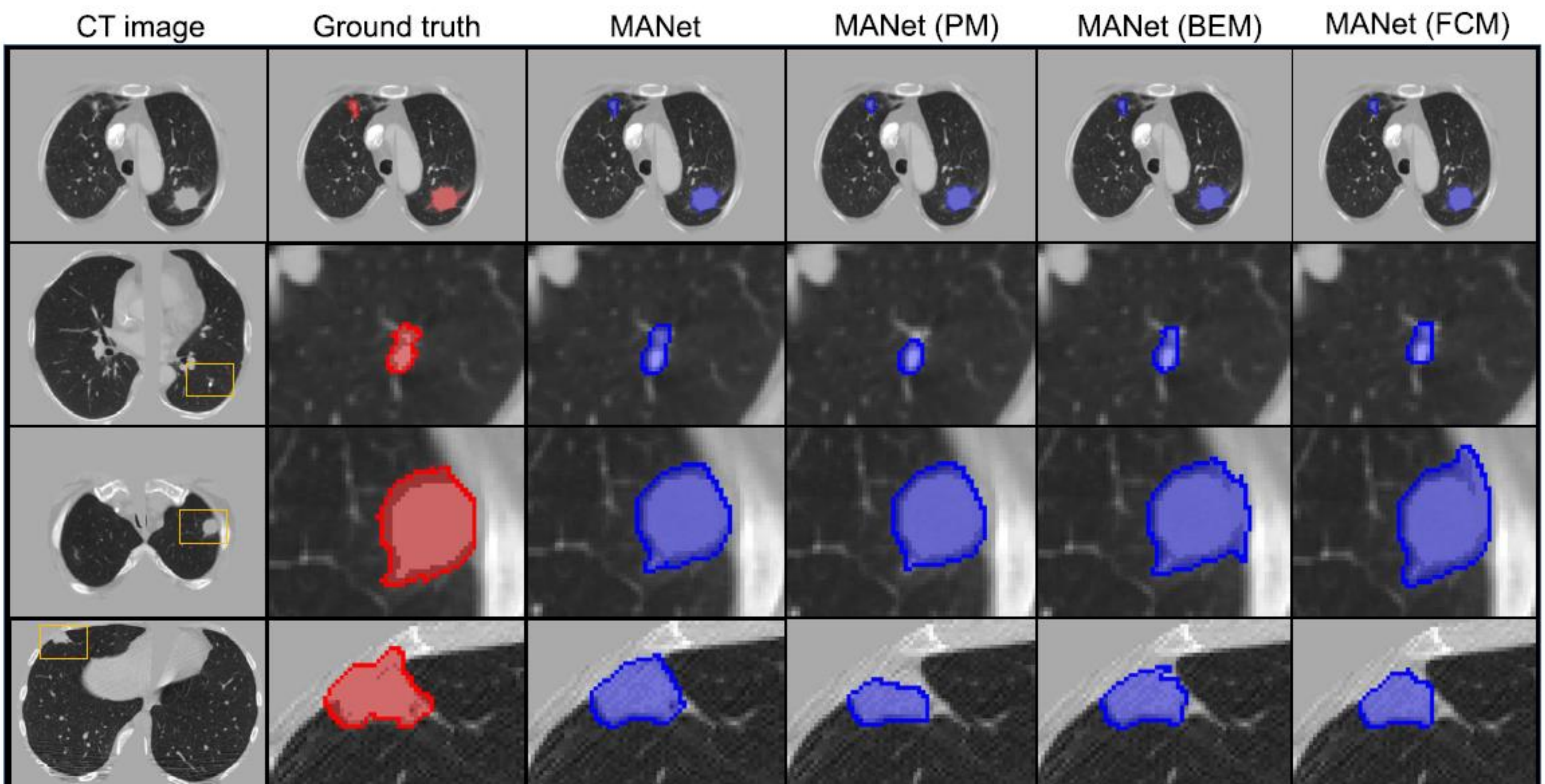
Further Development for Lung Nodule Detection and Segmentation

Tan-Cong Nguyen et al. **MANet: Multi-branch attention auxiliary learning for lung nodule detection and segmentation.** **Computer Methods and Programs in Biomedicine**. 241: 107748 (2023)

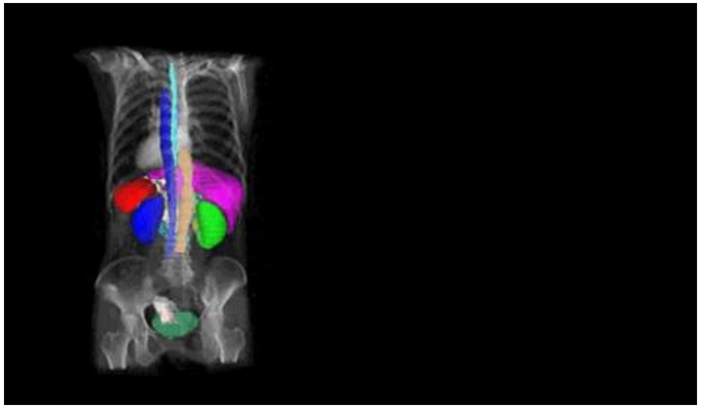


Further Development for Lung Nodule Detection and Segmentation

Tan-Cong Nguyen et al. **MANet: Multi-branch attention auxiliary learning for lung nodule detection and segmentation.**
Computer Methods and Programs in Biomedicine.
241: 107748 (2023)



Interactive Semi-supervised Abdominal Organ Segmentation in CT volume with Active Learning



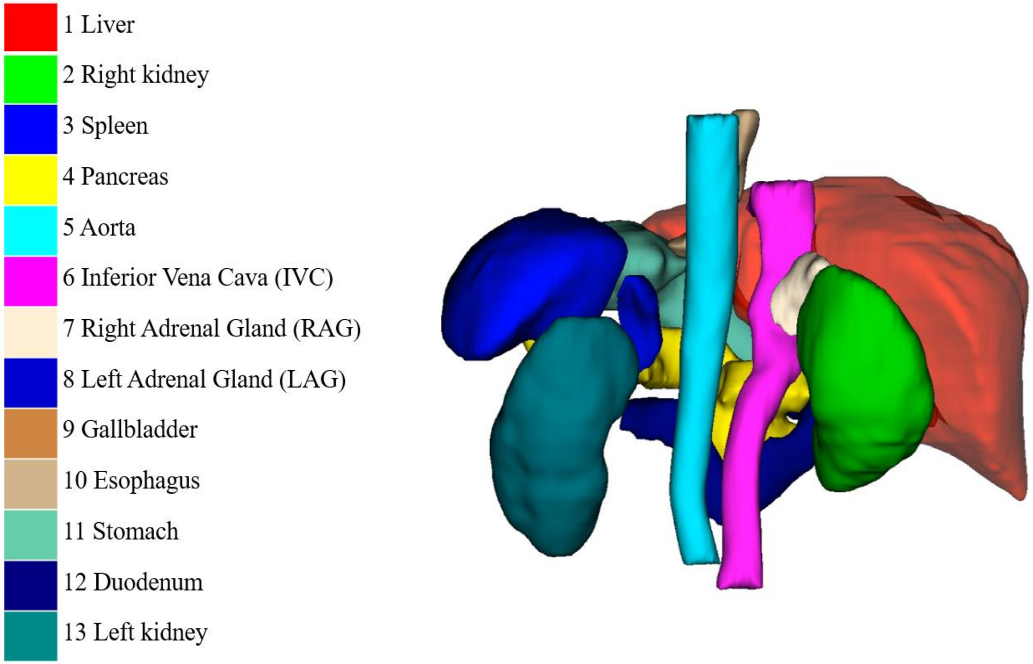
Minh-Khoi Pham, Thang-Long Nguyen-Ho, Thao Thi Phuong Dao, Tan-Cong Nguyen, Minh-Triet Tran:
Semi-supervised Organ Segmentation with Mask Propagation Refinement and Uncertainty Estimation for Data Generation.
FLARE@MICCAI 2022: 163-177

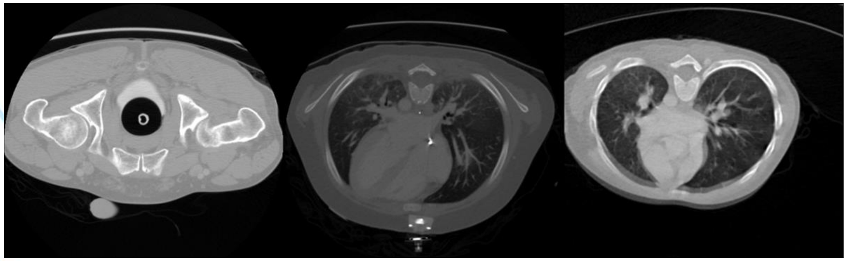
Overview

Dataset

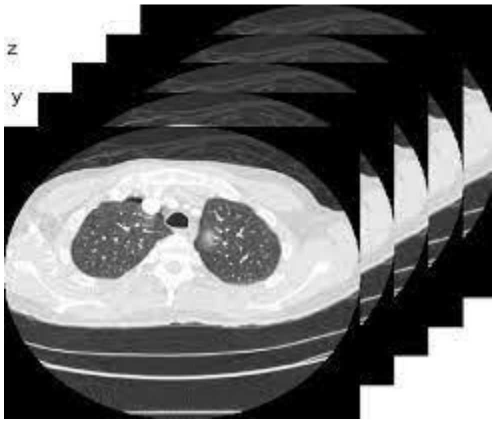
Fast and Low-resource semi-supervised Abdominal oRgan sEgmentation in CT

(FLARE22)





CT/MRI data?

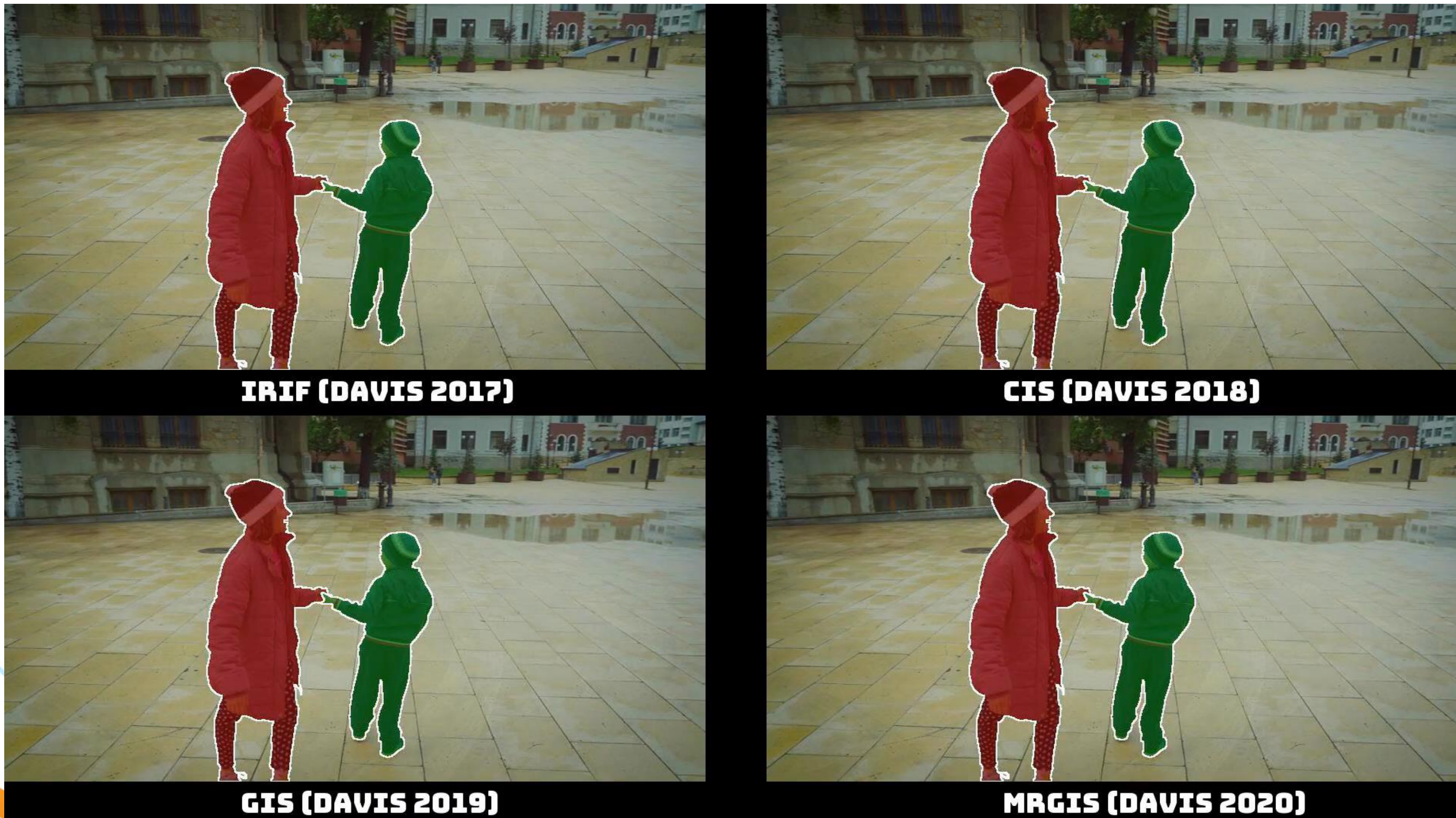


3D data ?
Sequence of 2D data?

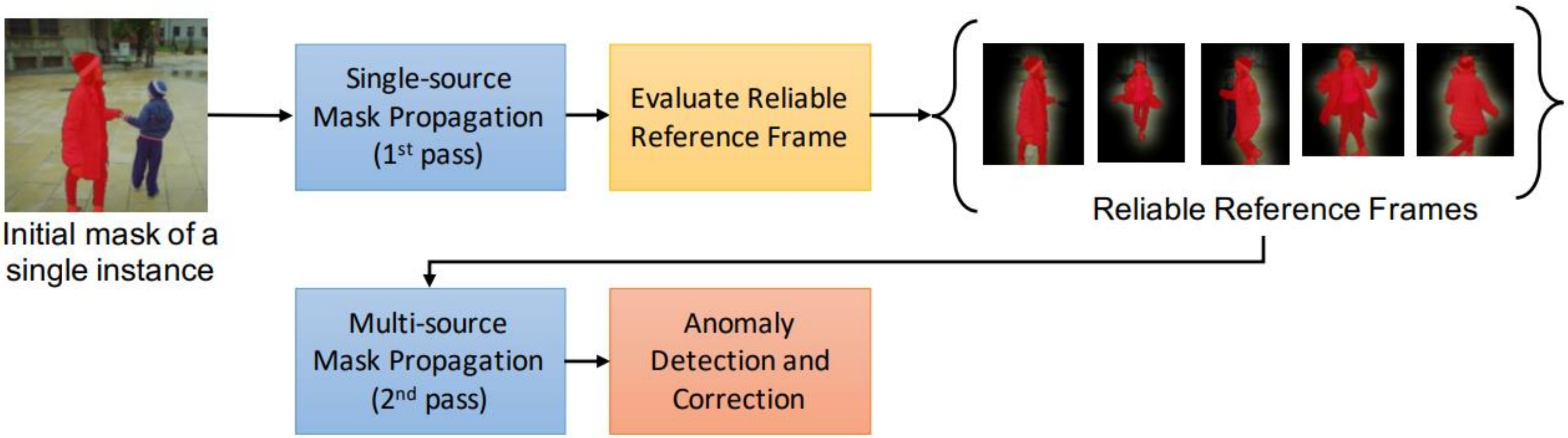
Intuition

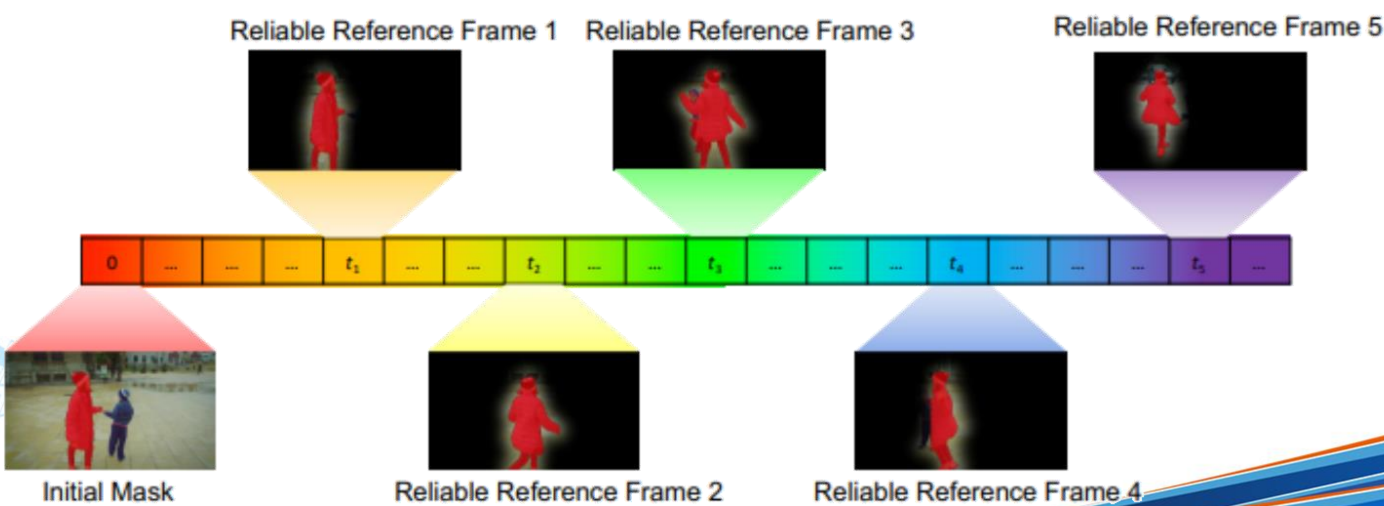
DAVIS: Densely Annotated VIdeo Segmentation (2017-2020)

- (Backward and Forward) Mask Propagation
- Starting Points (Seeds)?
- Guided Region-of-Interest (ROI)

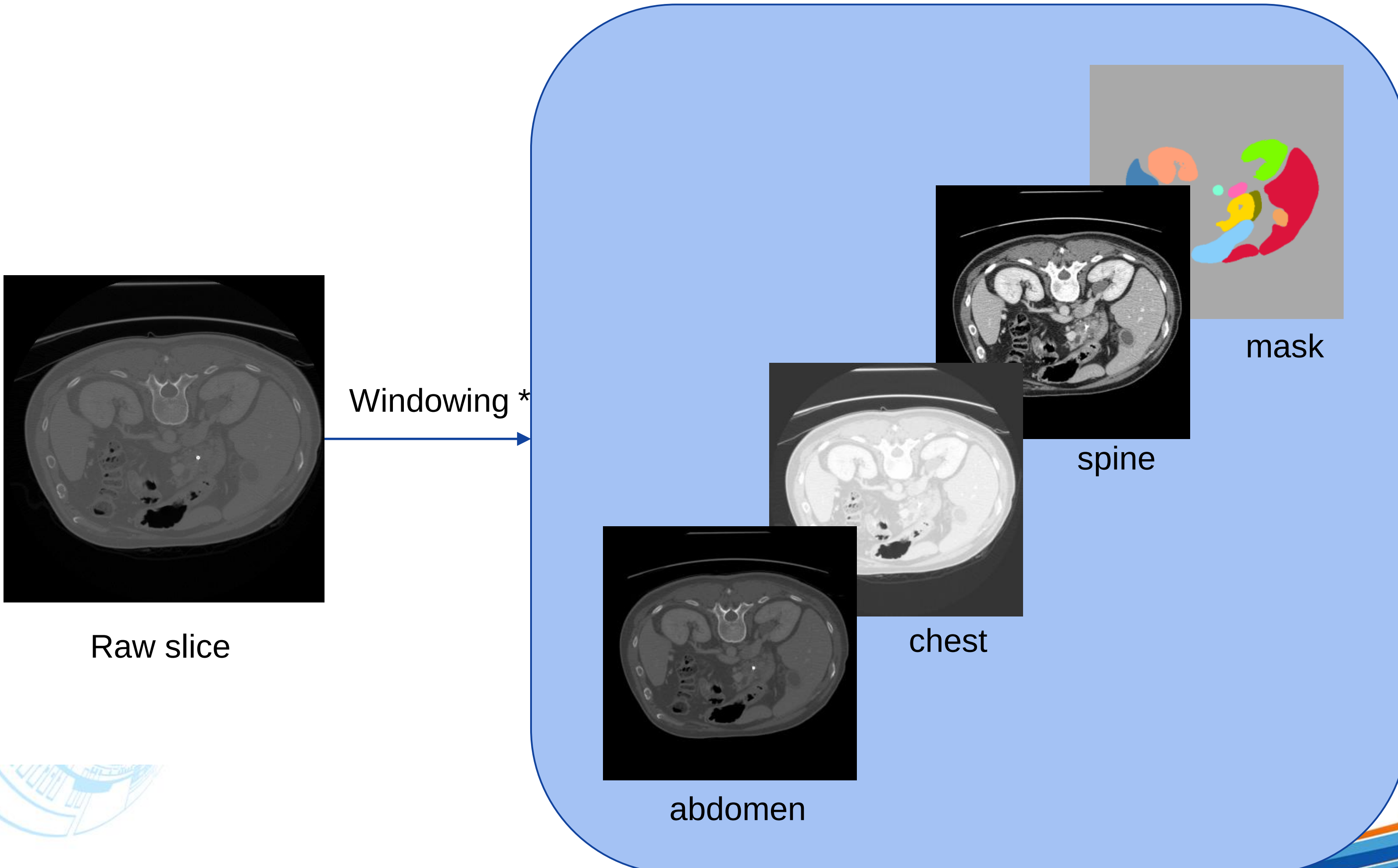


Mask Propagation…

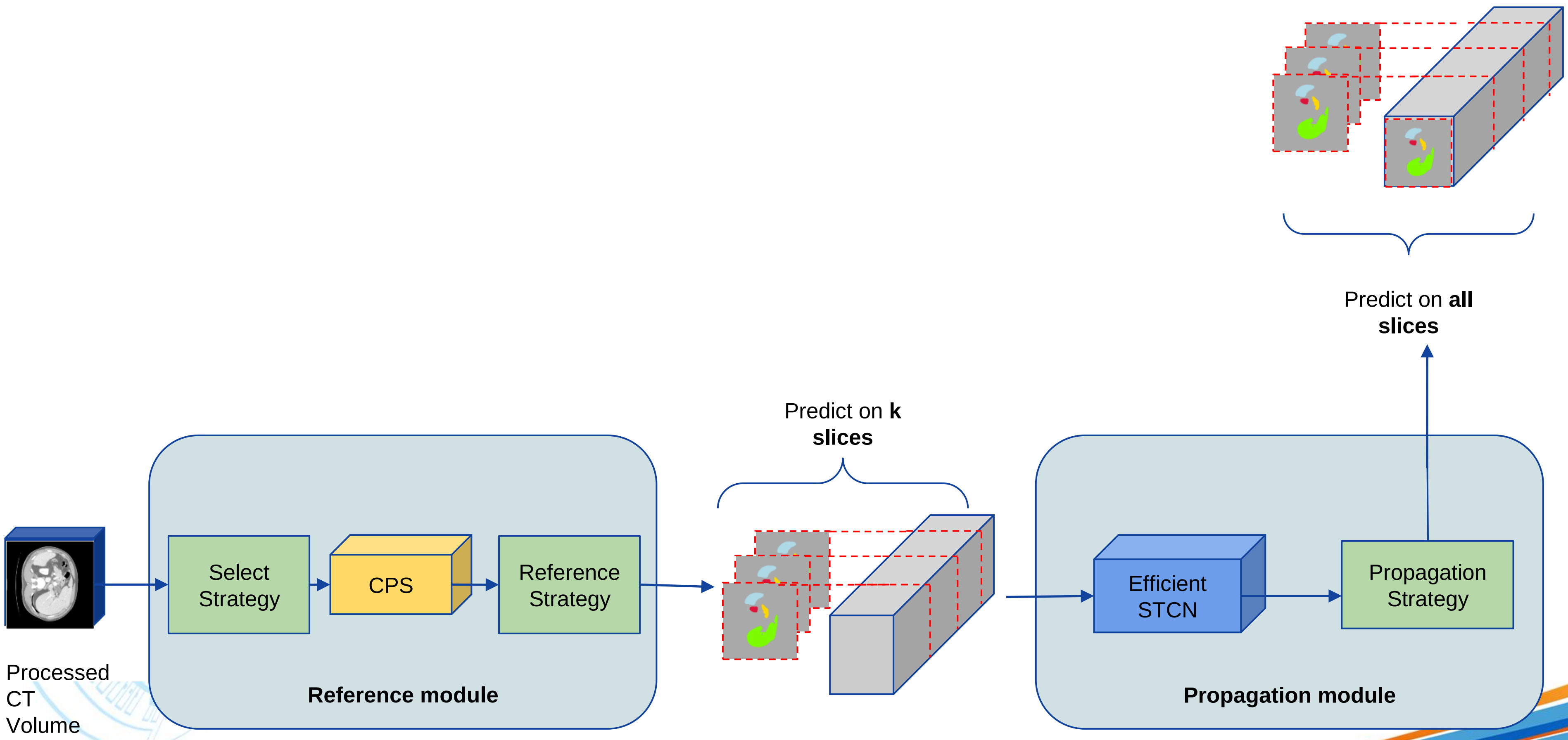




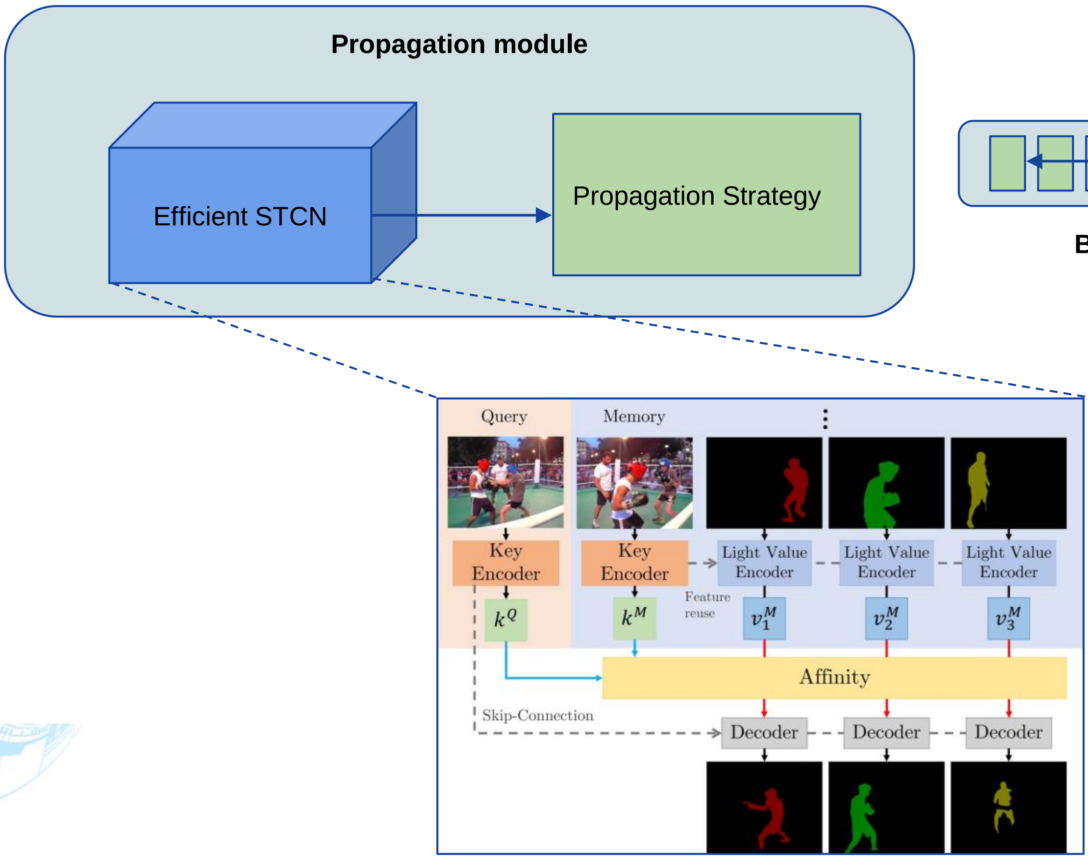
Preprocessing

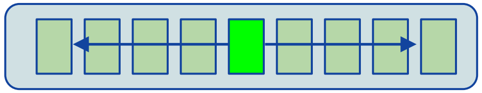


Method Overview



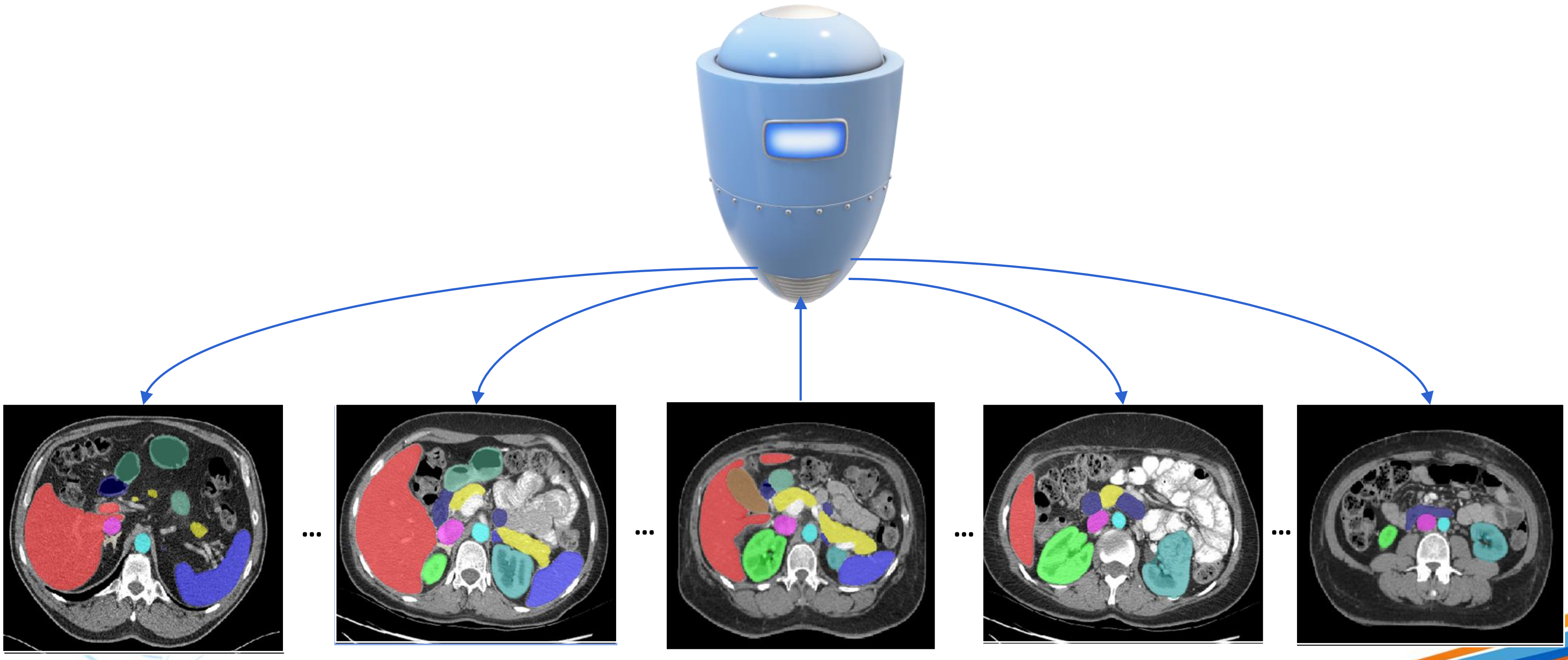
Propagation Module



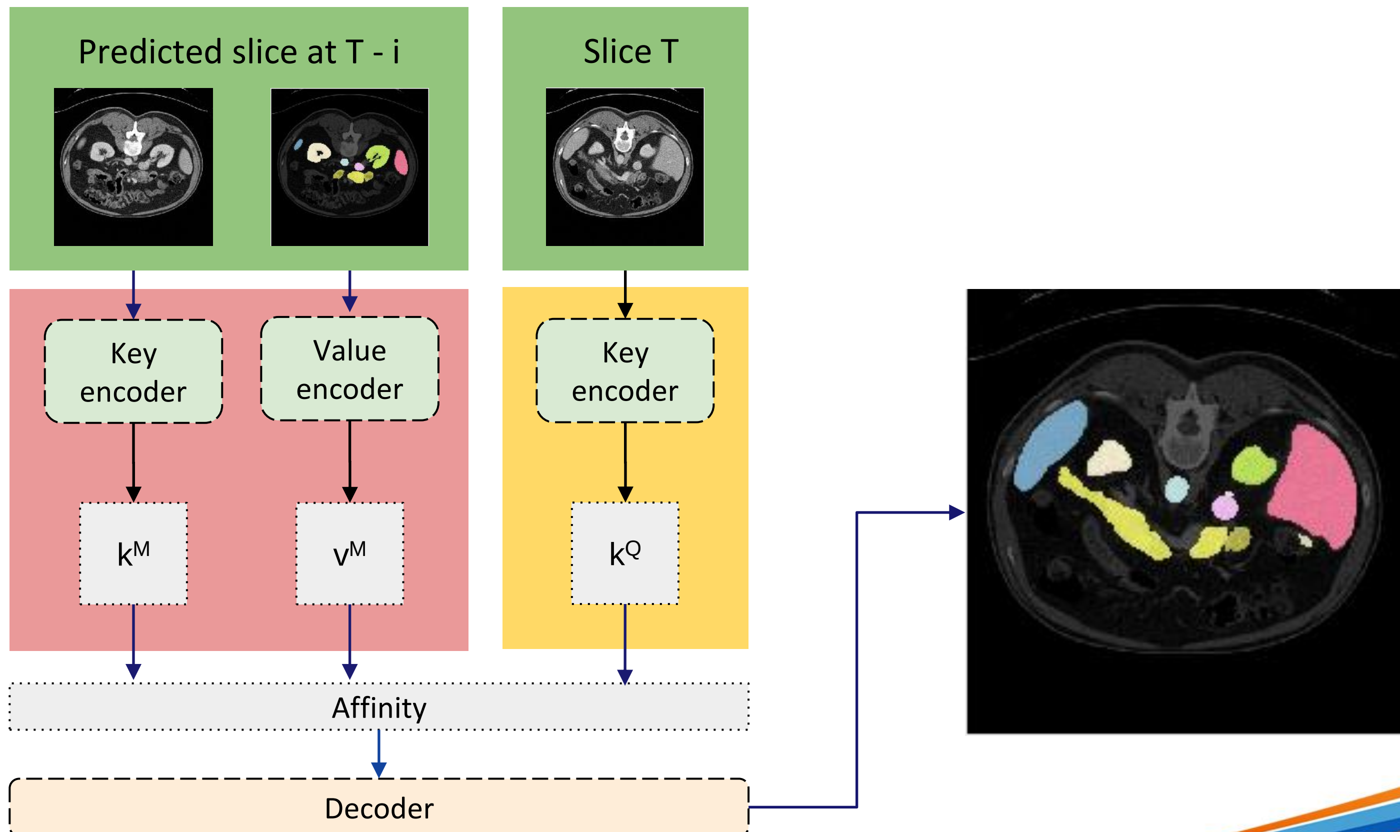


Bidirectional mask propagation

Propagation module

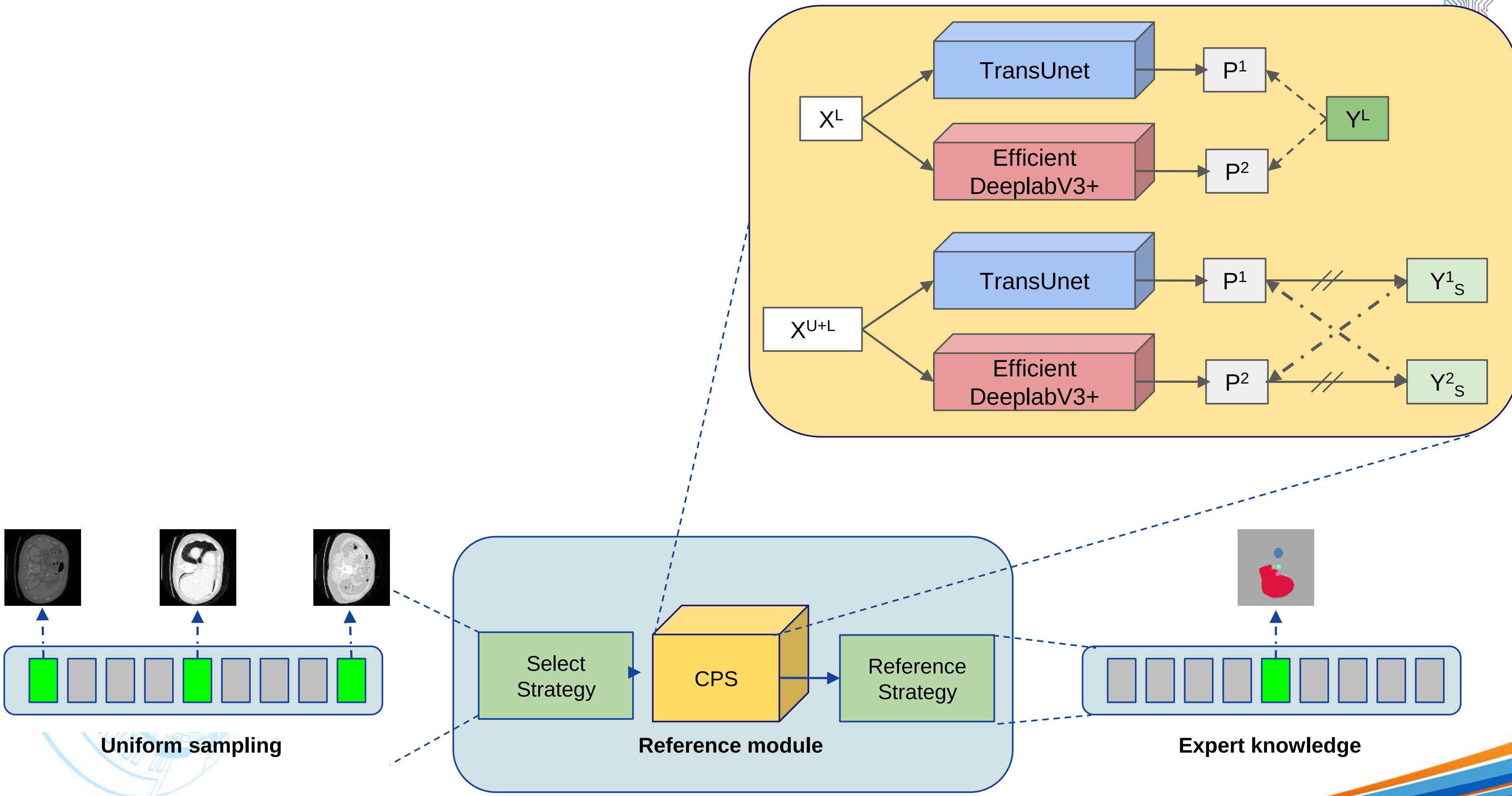


Propagation module



Rethinking Space-Time Networks with Improved Memory Coverage for Efficient Video Object Segmentation. NeurIPS 2021

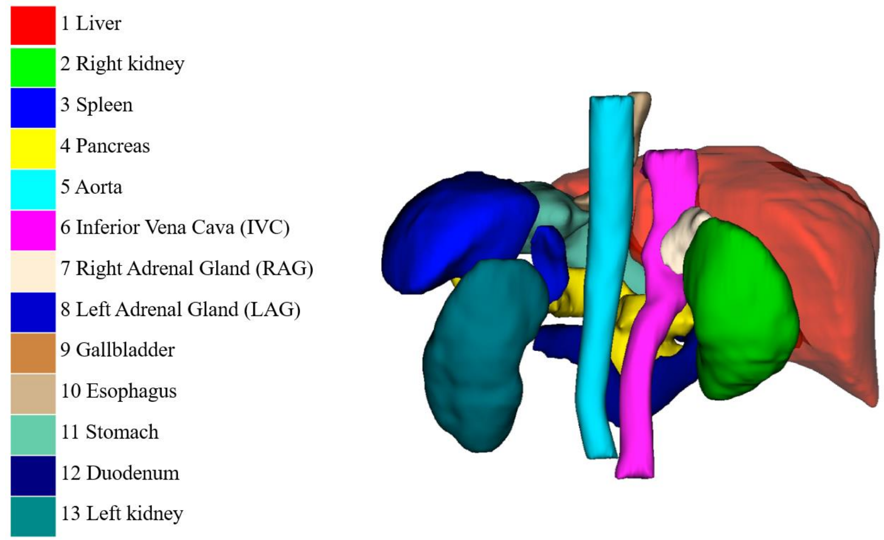
Reference Module/ What are Good Seeds?



Datasets

FLARE 2022

Fast and **L**ow-resource semi-supervised **A**bdominal o**R**gan s**E**gmentation in CT



50 labelled **2000 unlabelled**

Quantitative results

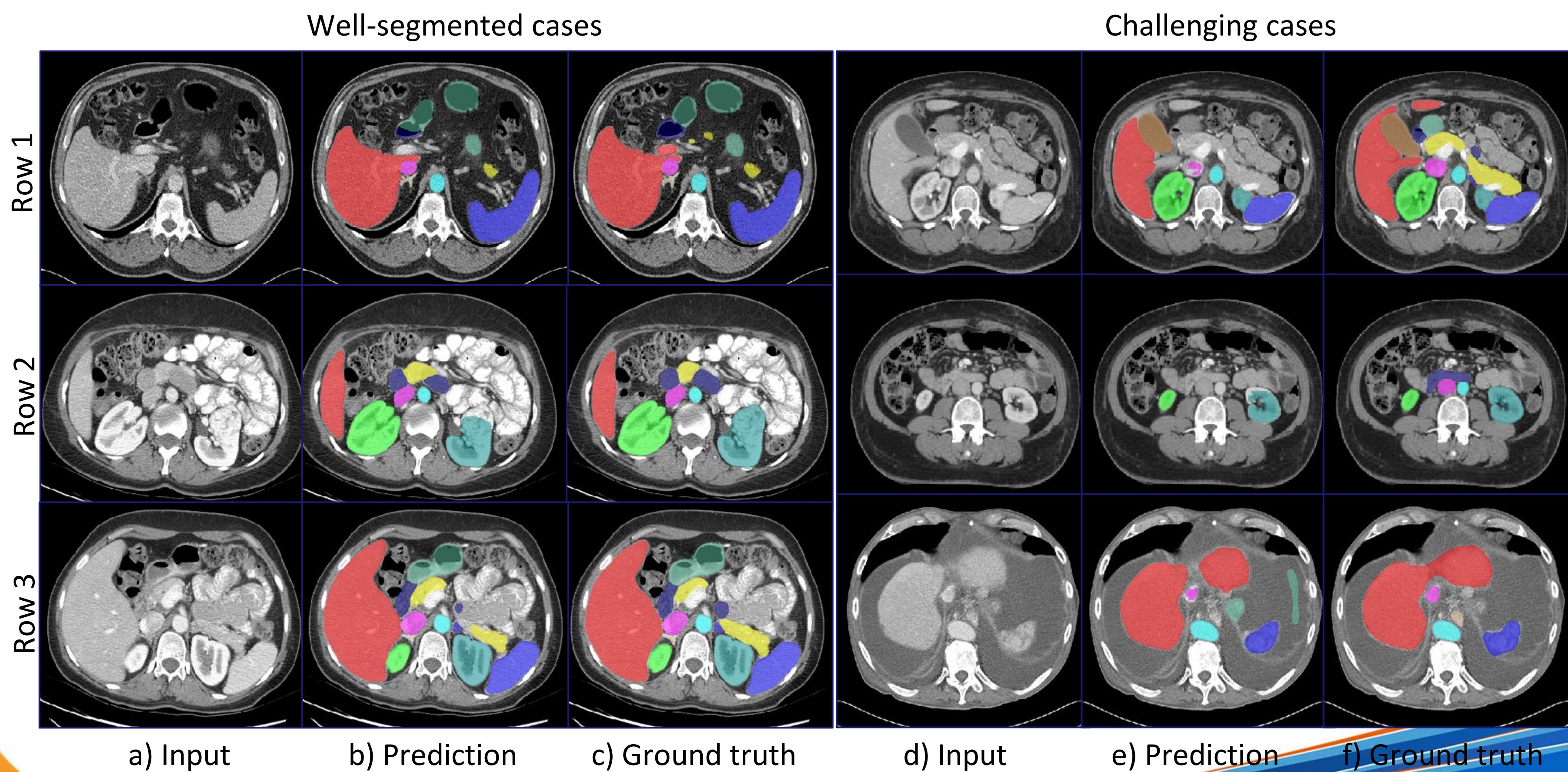
ID	CPS	Active learn-ing	Mask propa-gation	Mean DSC	Liver	RK	Spleen	Pancrease	Aorta	IVC	RAG	LAG	Gallbladder	Esophagus	Stomach	Duodenum	LK
1				**0.55**	0.90	0.68	0.70	0.49	0.70	0.57	0.32	0.25	0.43	0.48	0.61	0.29	0.71
2	x			0.76	0.95	0.80	0.91	0.70	0.93	0.80	0.67	0.62	0.55	0.80	0.82	0.56	0.80
3	x	x		0.77	0.96	0.81	0.92	0.73	0.93	0.80	0.66	0.62	0.60	0.78	0.84	0.56	0.80
4	x	x	x	**0.78**	0.96	0.81	0.92	0.76	0.94	0.82	0.66	0.61	0.6877	0.81	0.85	0.58	0.82

Dice Score evaluation on **public FLARE22 test set**

**First row, ensemble result of Unet and DeepLabv3+*

Qualitative results

PRELIMINARY RESULTS

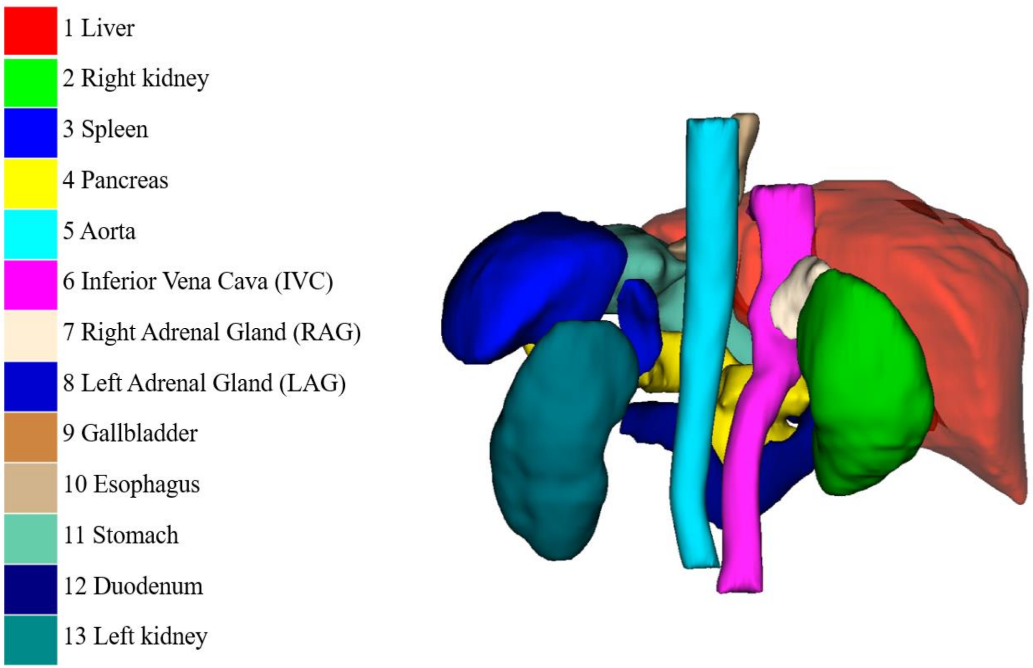


39
39

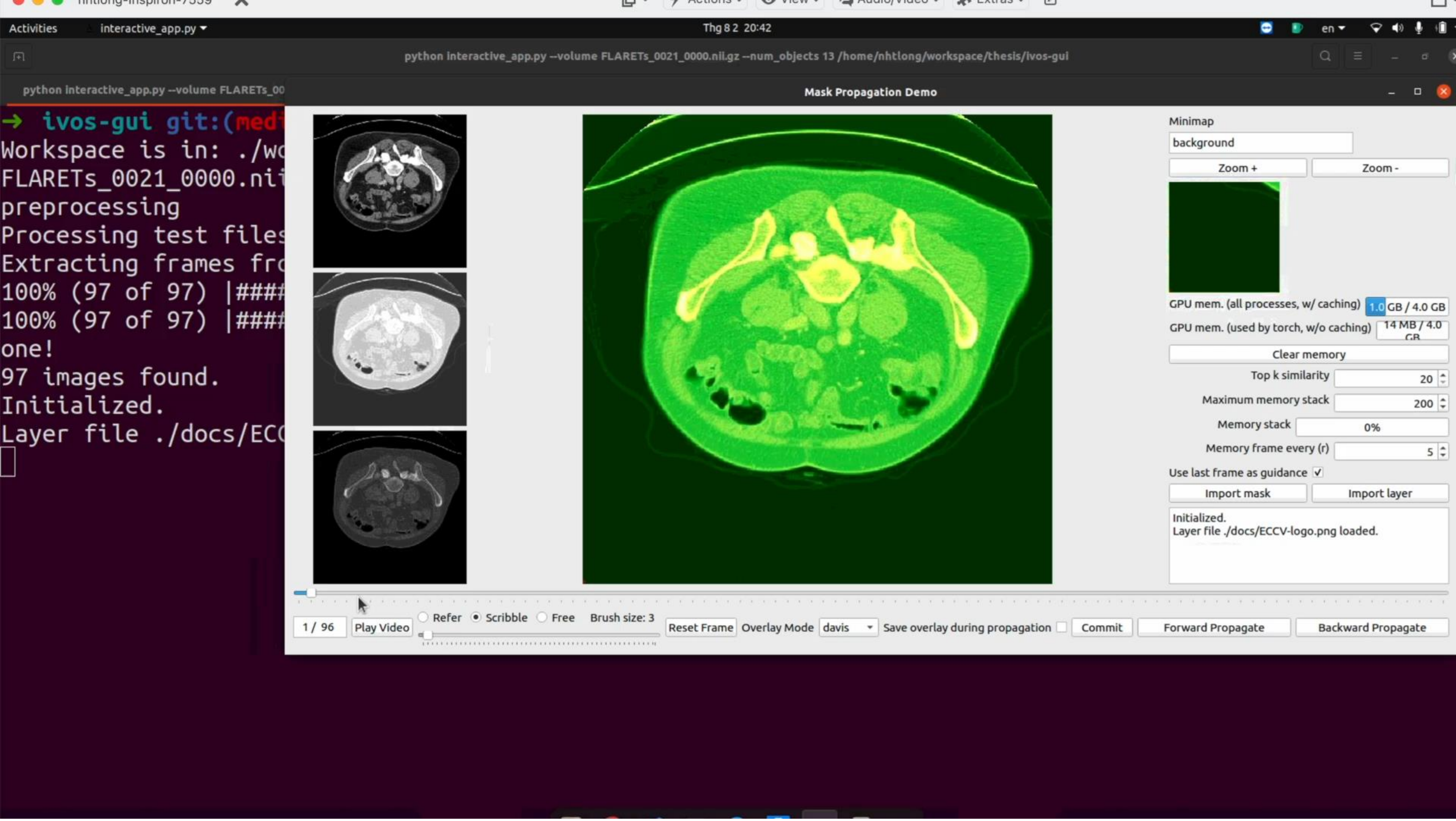
Brain Settings
Brain Threshold
353.00
Brain Opacity
0.20
Brain Smoothness
500
Image Intensity
2.00
Projection
Slicer
Axial Slice
Coronal Slice
Sagittal Slice
Mask Settings
Mask Opacity
1.00
Mask Smoothness
500
Multi Color
Single Color
Label 1
Label 2
Label 3
Label 4
Label 5
Label 6
Label 7
Label 8
Label 9
Label 10
Views
Axial
Coronal
Sagittal
Brain: FLARE22_Tr_0011_0000.nii.gz (min: -1024.00, max: 1730.00)
Mask: FLARE22_Tr_0011.nii.gz

How to Improve?

- ❖ Where the organ can be?
- ❖ Where the organ can be best observed?
- ❖ Inter-Relationship between organs?



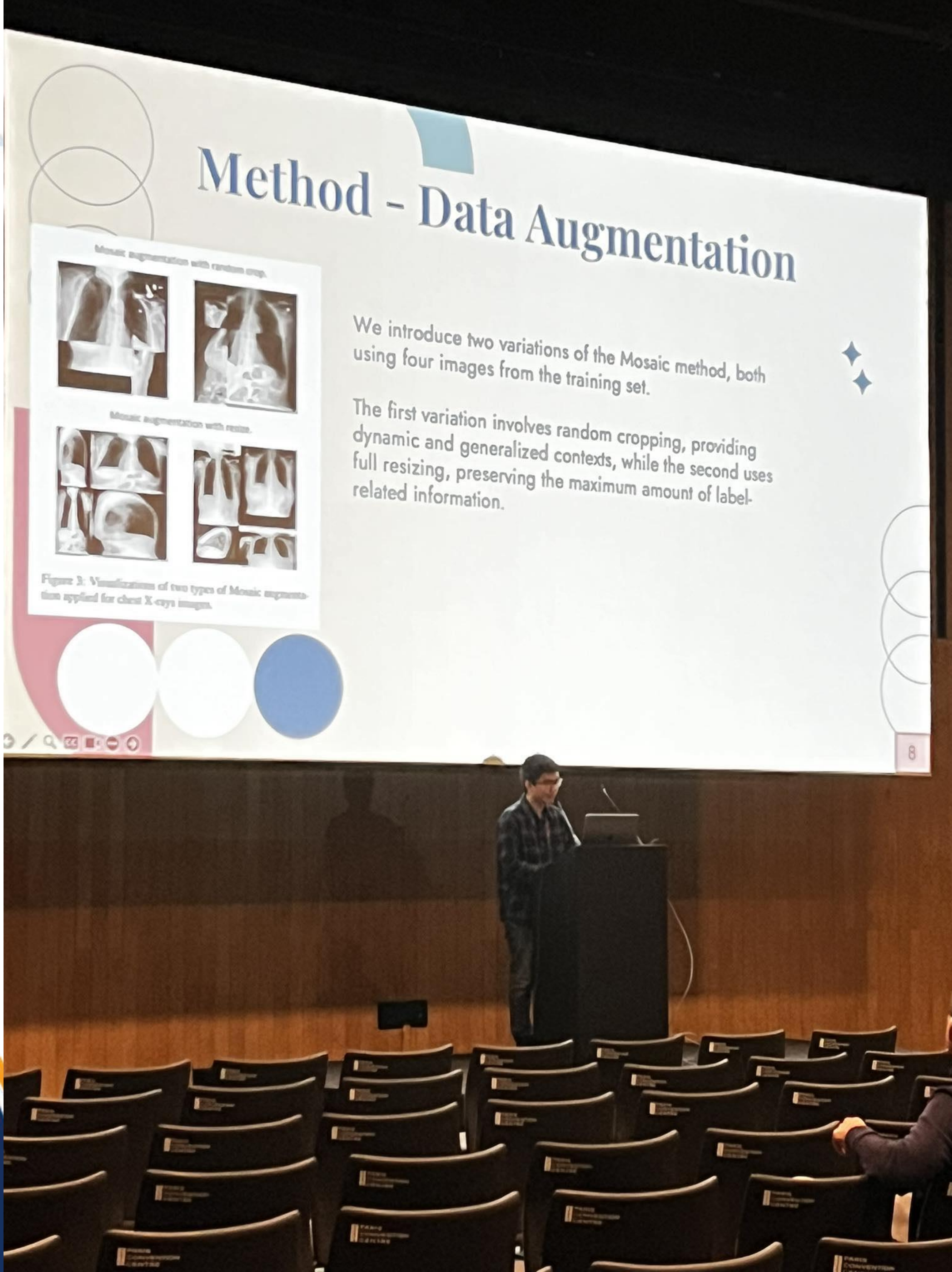
1/ esophagus, stomach, and duodenum
2/ right adrenal gland, and right renal
3/ left adrenal gland and left renal
4/ liver + gallbladder
5/ pancreas + spleen
6/ aorta + IVC



Activities
interactive_app.py
Thg 8 2 20:42
python interactive_app.py --volume FLARETs_0021_0000.nii.gz --num_objects 13 /home/nhtlong/workspace/thesis/ivos-gui
Mask Propagation Demo
→ ivos-gui git:(medi
Workspace is in: ./wo
FLARETs_0021_0000.nii
preprocessing
Processing test files
Extracting frames fro
100% (97 of 97) |####
100% (97 of 97) |####
one!
97 images found.
Initialized.
Layer file ./docs/ECC
Minimap
background
Zoom +
Zoom -
GPU mem. (all processes, w/ caching)
1.0 GB / 4.0 GB
GPU mem. (used by torch, w/o caching)
14 MB / 4.0 GB
Clear memory
Top k similarity
20
Maximum memory stack
200
Memory stack
0%
Memory frame every (r)
5
Use last frame as guidance
Import mask
Import layer
Initialized.
Layer file ./docs/ECCV-logo.png loaded.
1 / 96
Play Video
Refer
Scribble
Free
Brush size: 3
Reset Frame
Overlay Mode
davis
Save overlay during propagation
Commit
Forward Propagate
Backward Propagate

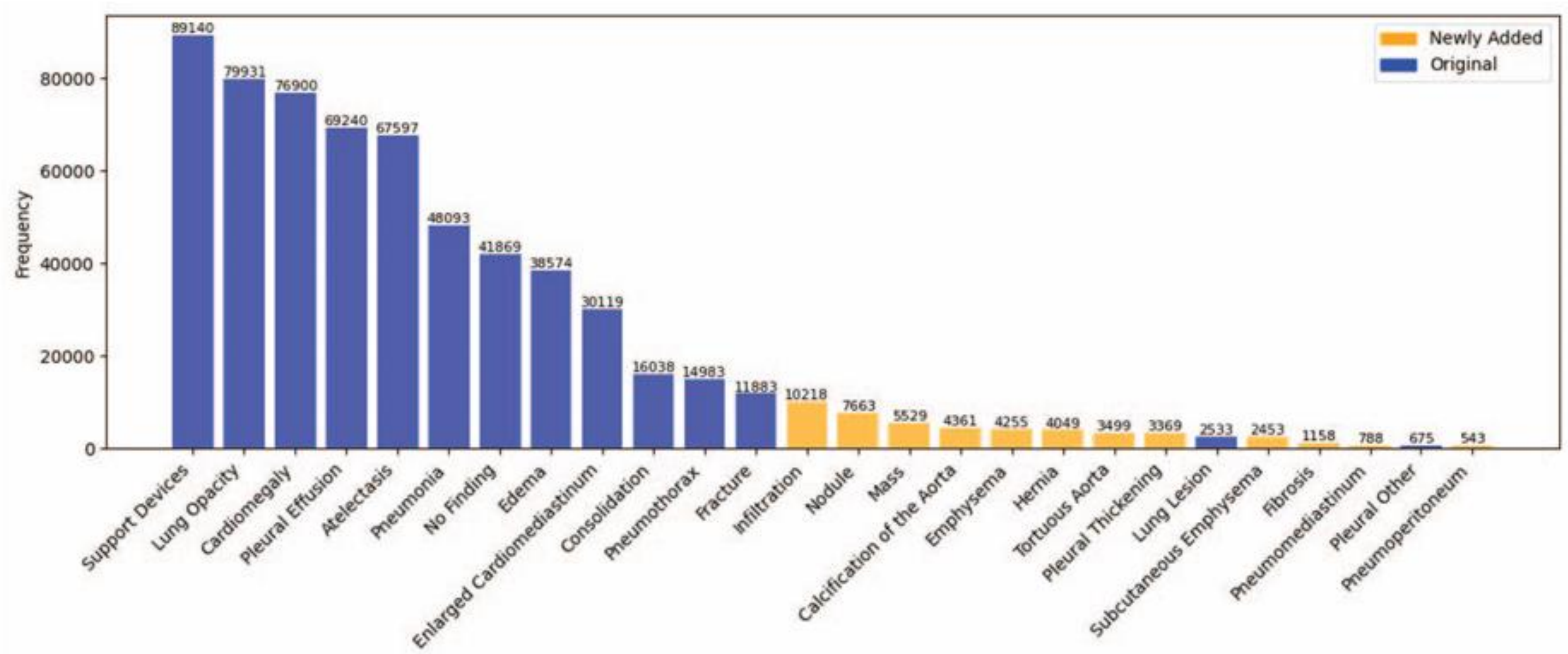
Advanced Augmentation and Ensemble Approaches for Classifying Long-Tailed Multi-Label Chest X-Rays

Trong-Hieu Nguyen Mau, Tuan-Luc Huynh, Thanh-Danh Le, Hai-Dang Nguyen, Minh-Triet Tran: **Advanced Augmentation and Ensemble Approaches for Classifying Long-Tailed Multi-Label Chest X-Rays**. **ICCV (Workshops) 2023:** 2721-2730



VNUHCM Students
@ICCV 2023 in France

Long-Tailed Multi-Label Chest X-Rays



Our Enhanced Results…

Baseline: Pleural Effusion, Support Devices
Our: Atelectasis, Pleural Effusion, Support Devices
Ground truth: Atelectasis, Pleural Effusion, Support Devices

Baseline: Edema, Pleural Effusion
Our: Cardiomegaly, Pleural Effusion
Ground truth: Cardiomegaly, Pleural Effusion

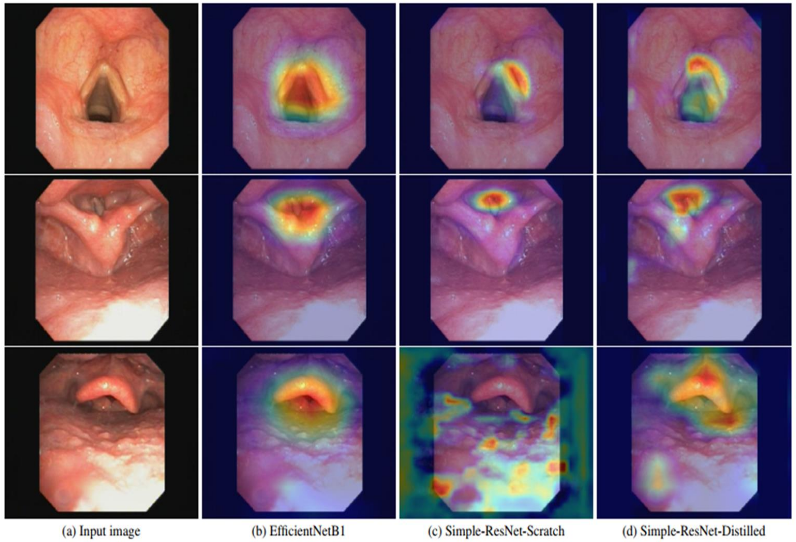
Baseline: Atelectasis, Pleural Effusion
Our: Atelectasis
Ground truth: Atelectasis

Baseline: Lung Opacity
Our: Fibrosis, Lung Opacity, Support Devices
Ground truth: Fibrosis, Lung Opacity, Support Devices

Baseline: ***No Finding***
Our: Nodule, Support Devices
Ground truth: Nodule, Support Devices

Baseline: ***No Finding***
Our: Hernia
Ground truth: Hernia

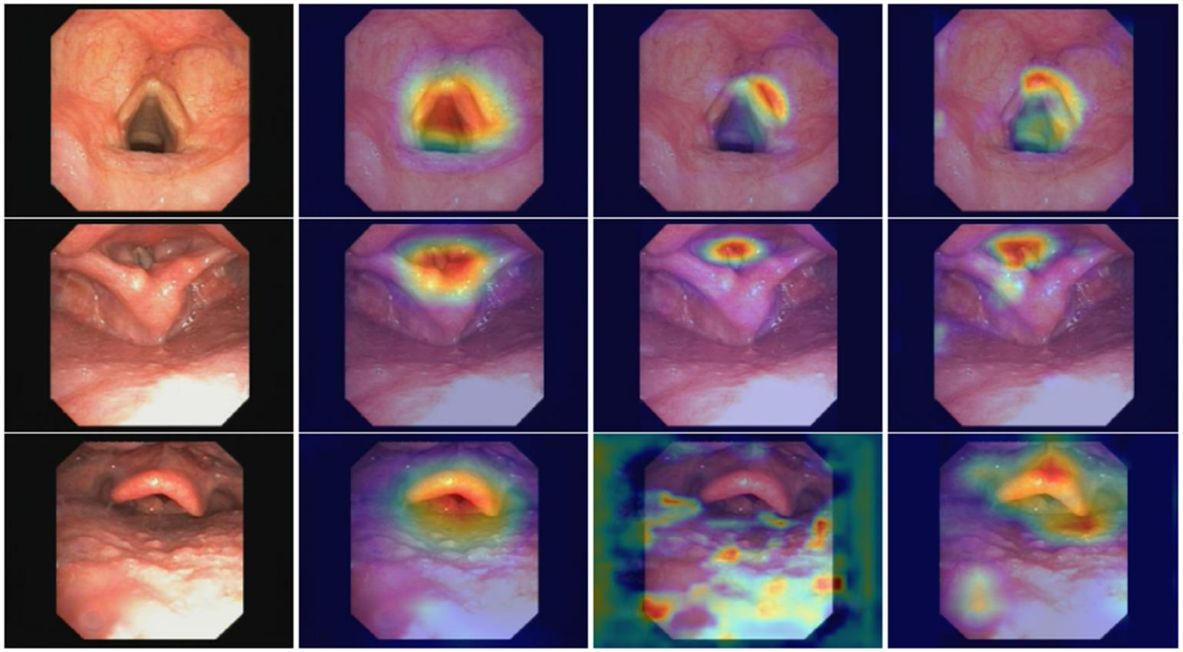
Vision-based Assistance for Vocal Fold Identification in Laryngoscopy with Knowledge Distillation



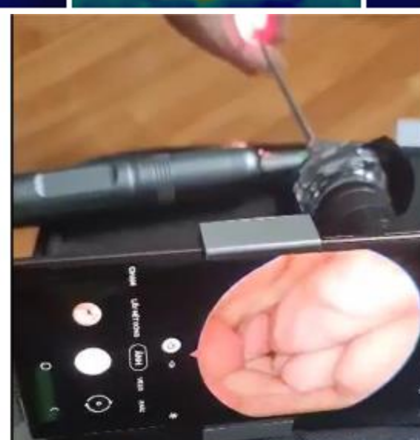
Thao Dao et al.:
Vision-based Assistance
for Vocal Fold Identification in Laryngoscopy with Knowledge Distillation
MedInfo23

Portable Laryngoscope with AI Smart Assistance

Thao Thi Phuong Dao et al.
Journal of Imaging Informatics in Medicine, 2024

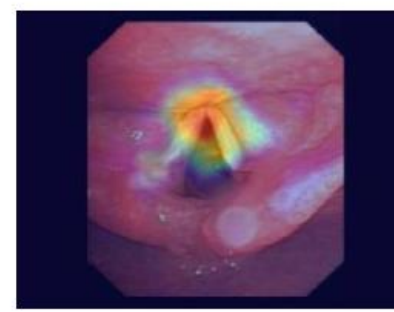


(a) Input image (b) EfficientNet



Images from laryngoscope connected to smartphone

AI Smart Assistance in Mobile

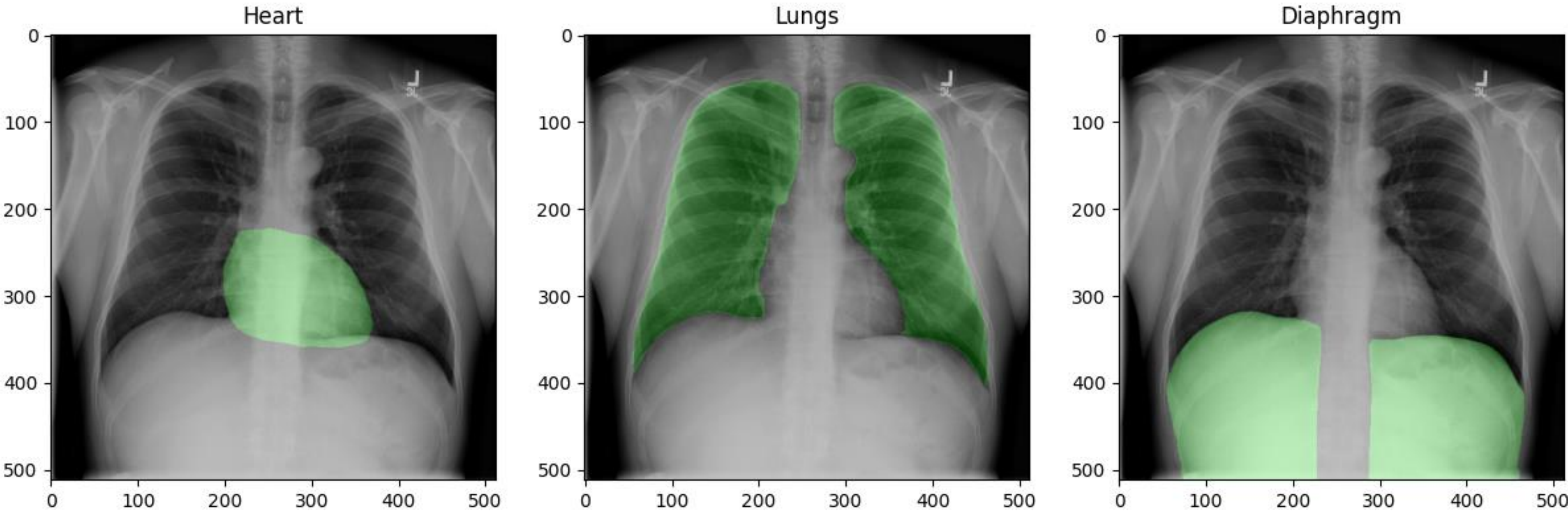


Vocal folds located in image in realtime

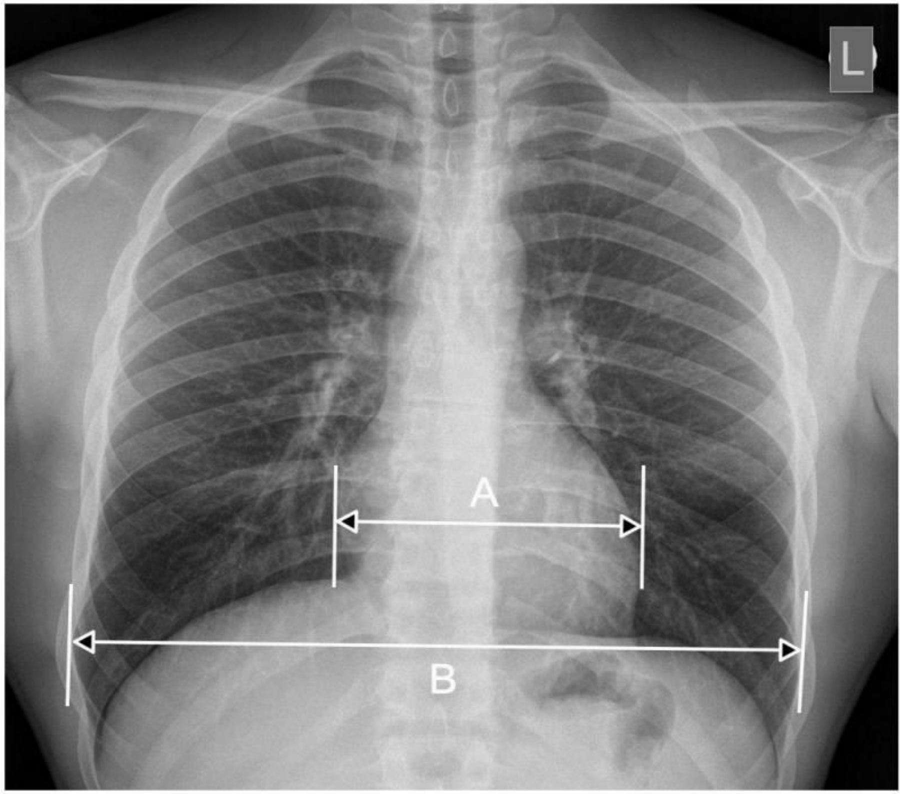
Combining Deep Learning And Medical Knowledge to Detect Cardiomegaly and Pleural Effusion in Chest X-rays Diagnosis.

Dai-Nghia Nguyen, Lan-Anh Le-Pham, Hai-Dang Nguyen, Minh-Triet Tran: Combining Deep Learning And Medical Knowledge to Detect Cardiomegaly and Pleural Effusion in Chest X-rays Diagnosis. **SoICT 2023**: 562-569

Explanable AI?

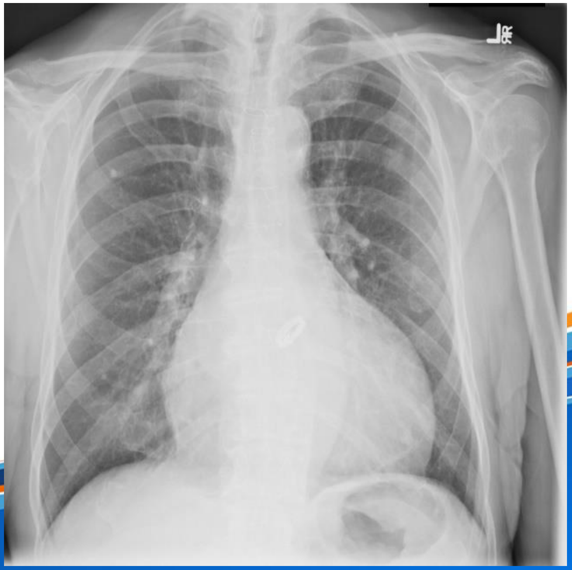


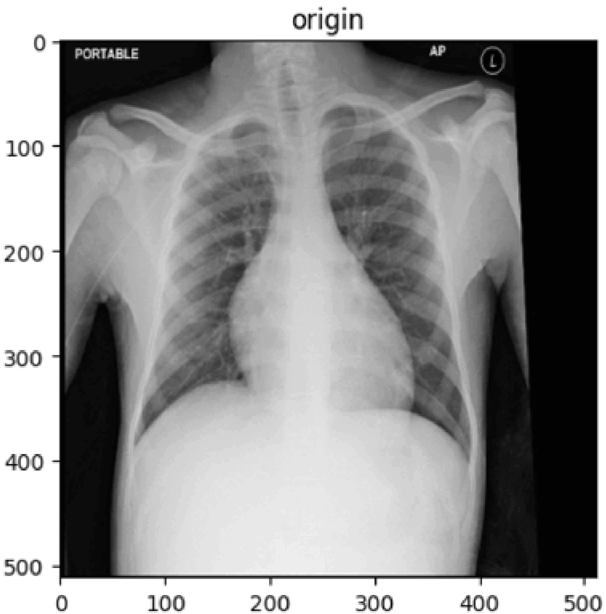
Domain Knowledge



CTR = **0.597**

CTR = **0.618**




origin
PORTABLE
AP
0
100
200
300
400
500

Conclusion

- Experts and Domain Knowledge
- Collaboration
- Data and Annotated Data
- New Generation and Future
- …

53

Thank you for your attention