MedTech Innovation

Machine Learning-Based Models for Interpreting IVUS

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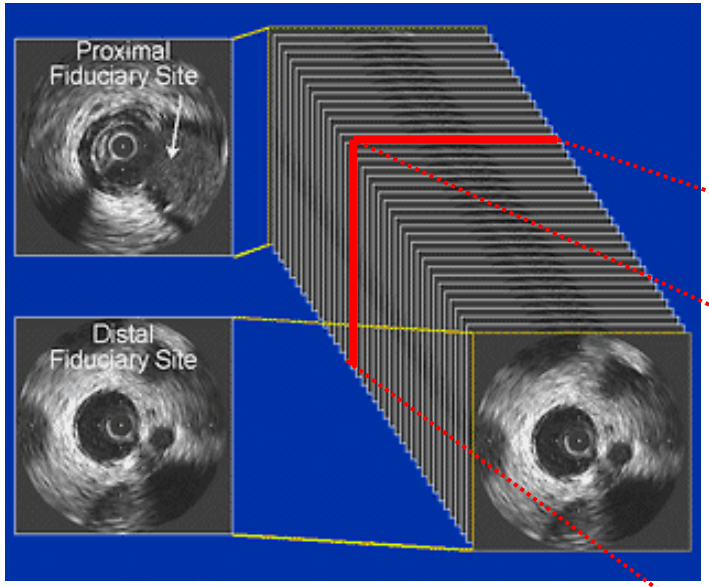
Disclosure

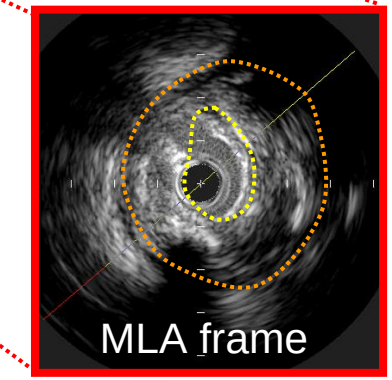
I, Soo-Jin Kang DO NOT have a financial interest/arrangement or affiliation with one or more organizations that could be perceived as a real or apparent conflict of interest in the context of the subject of this presentation

Issues for IVUS Analysis

- Time & cost for frame-by-frame analysis
- Intra- & inter-observer variabilities
- Predictors derived from a single frame

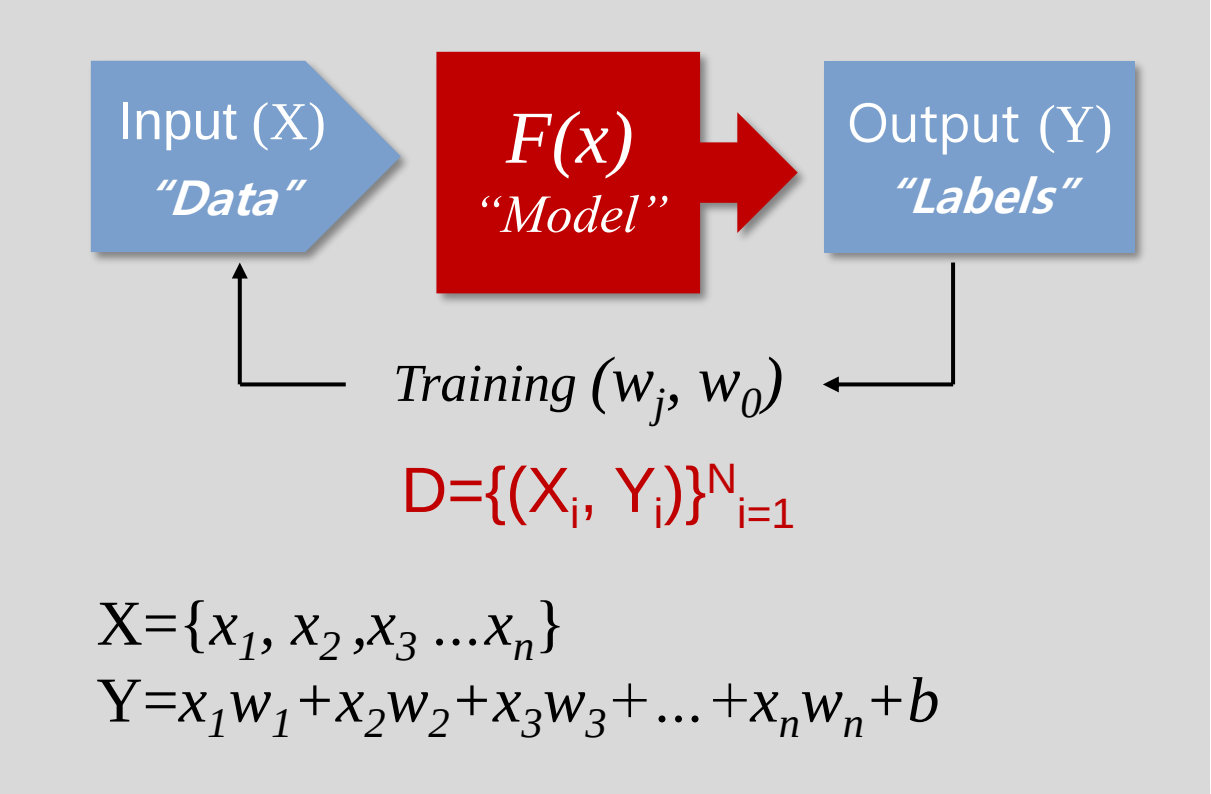


Automated program for whole frame analysis



Supervised Machine Leaning (ML)

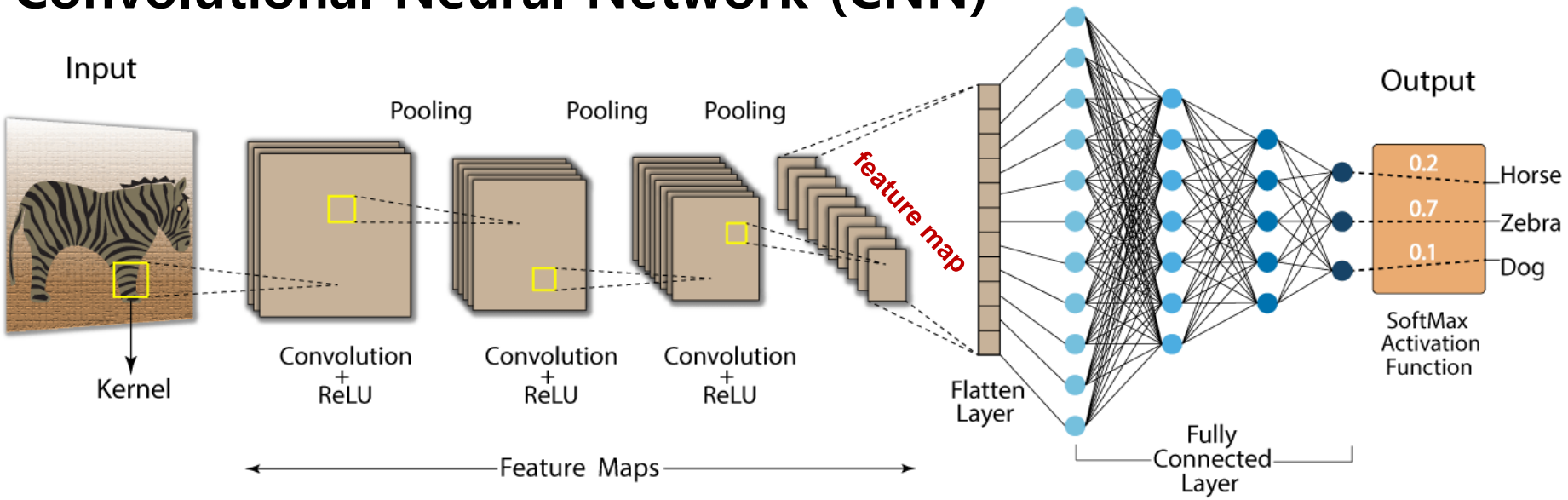
enables computers to learn from data & to make a model



- Non-linearity between variables & outcomes
- Interactions among variables
- Too many variables

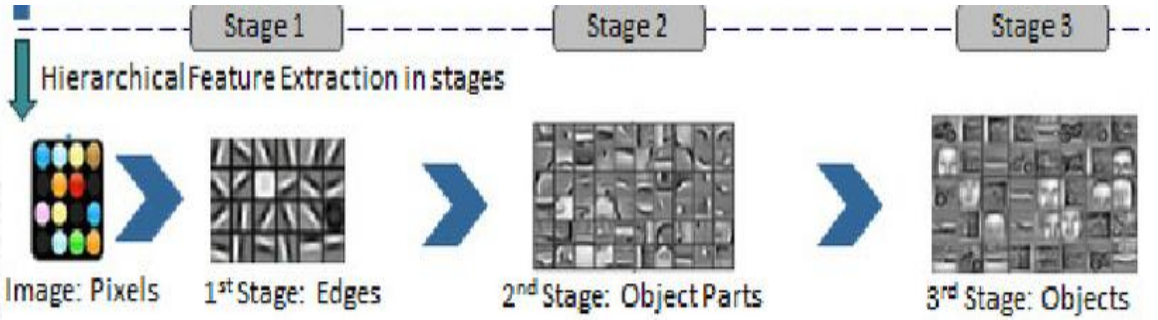
Deep Learning (DL)

Convolutional Neural Network (CNN)



Feature Extraction (by CONV)

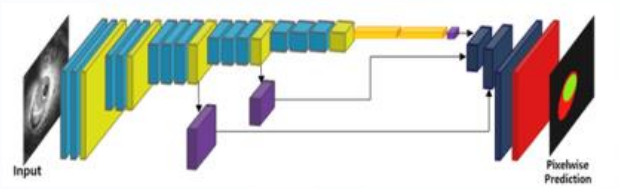
Classification (by ANN)



- A data-driven approach that is based on a set of algorithms to model high-level abstractions in data by using multiple processing layers composed of non-linear transformations
- 'End-to-end learning'

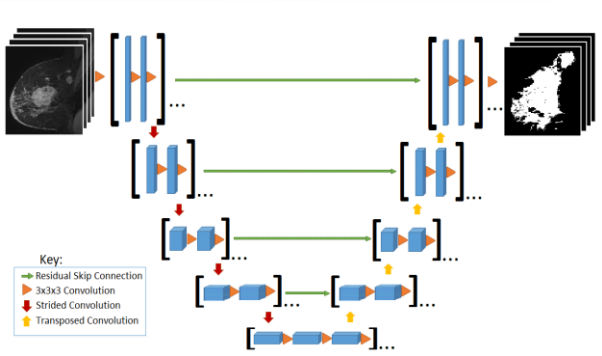
Automatic IVUS Segmentation by DL

FCN-all-at-once-VGG16 (2017)

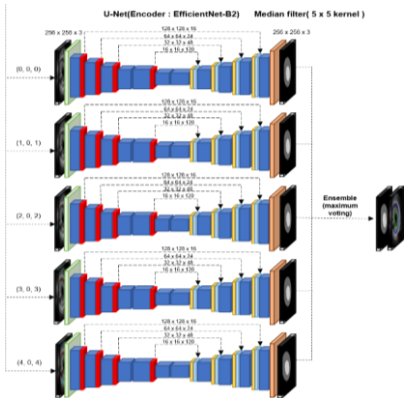


- 1240 IVUS pullbacks (191,407 frames)
- Manual annotation of lumen & EEM at 0.4-mm interval

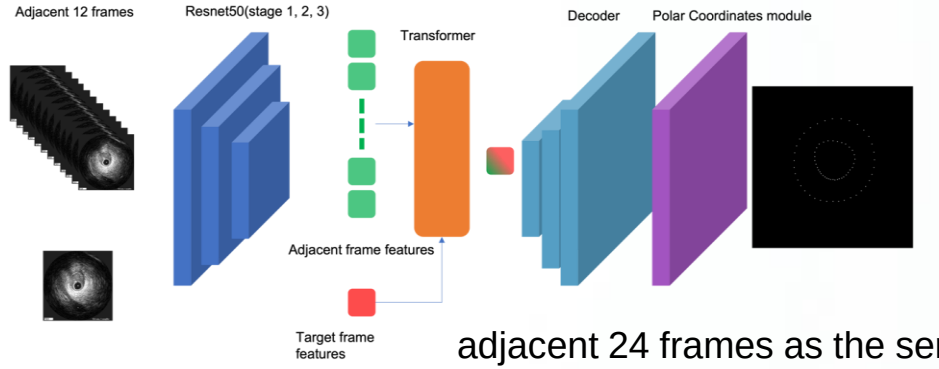
UNet (2019)



Efficient-UNet (2021)



ResNet-Transformer (2023)

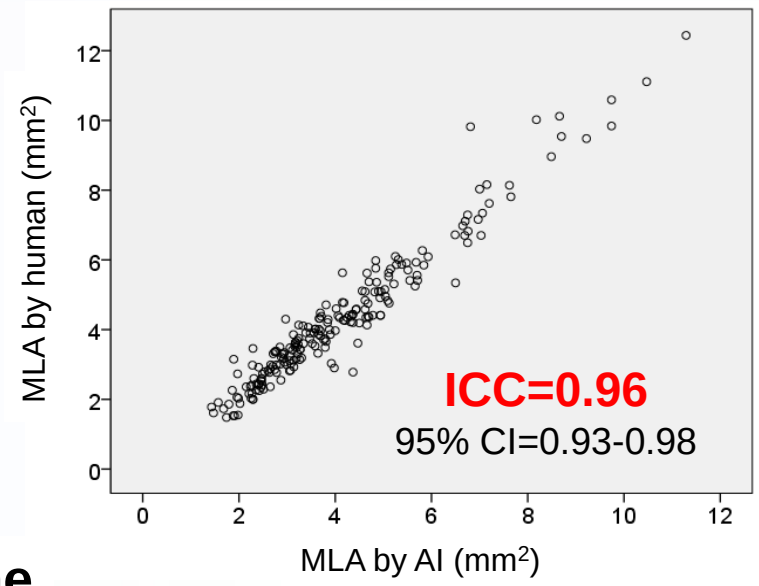


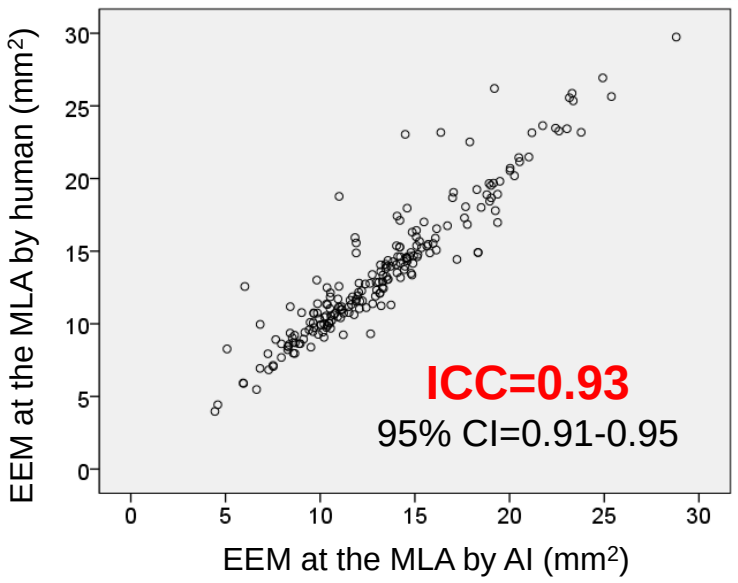
adjacent 24 frames as the serial input

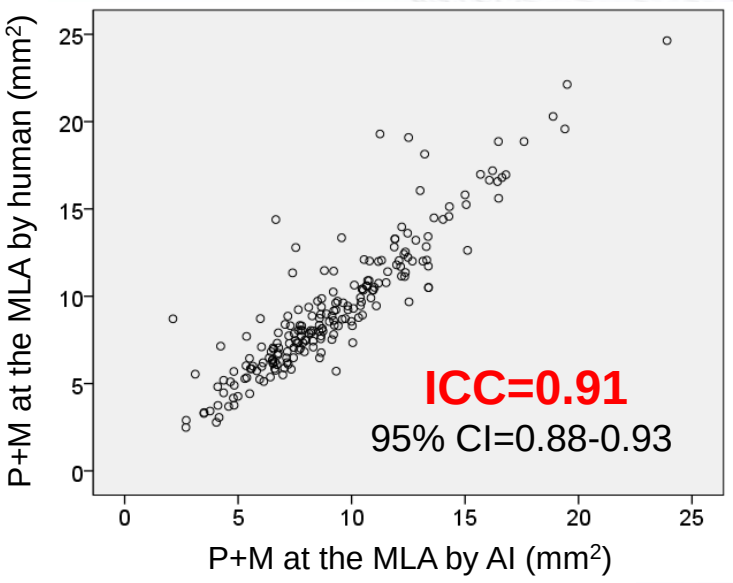
Frame-level in the test set	Lumen		EEM	
	DSC	JI	DSC	JI
Within bifurcation	0.94±0.01	0.89±0.02	0.89±0.01	0.80±0.02
Non-bifurcation	0.97±0.00	0.94±0.00	0.94±0.00	0.89±0.00

AI (Whole Frames) vs. Human (at 0.5-mm interval)

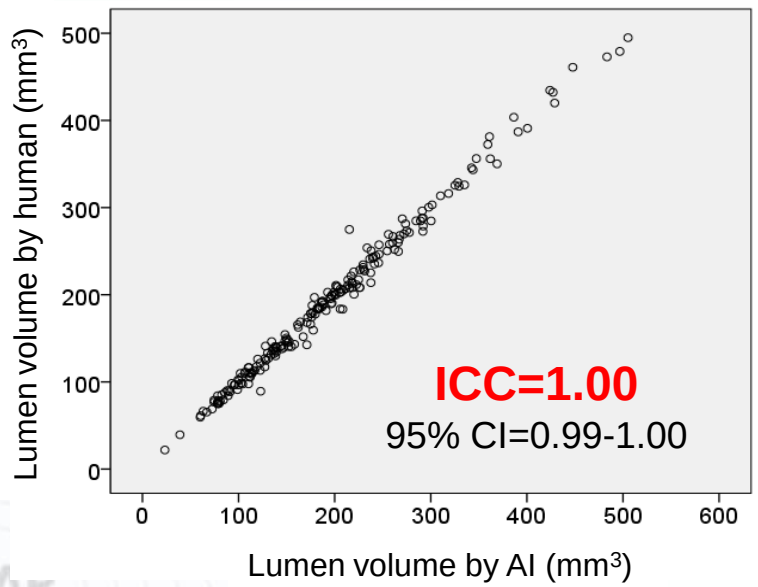
Area

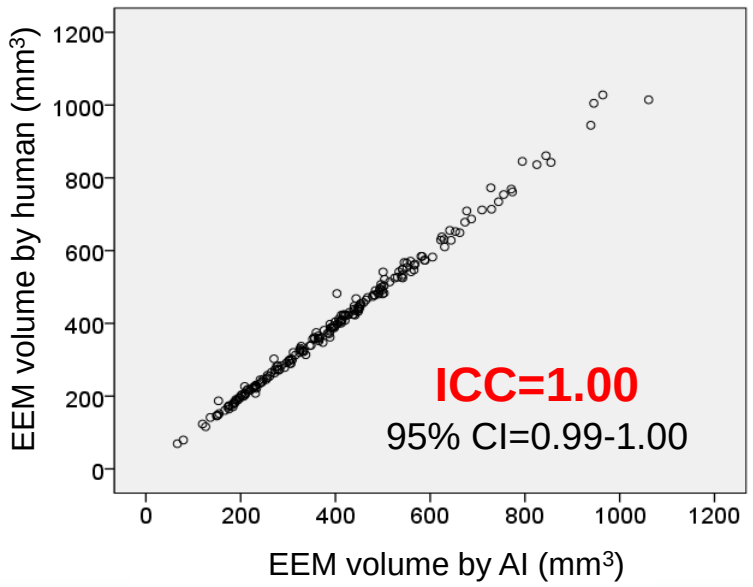


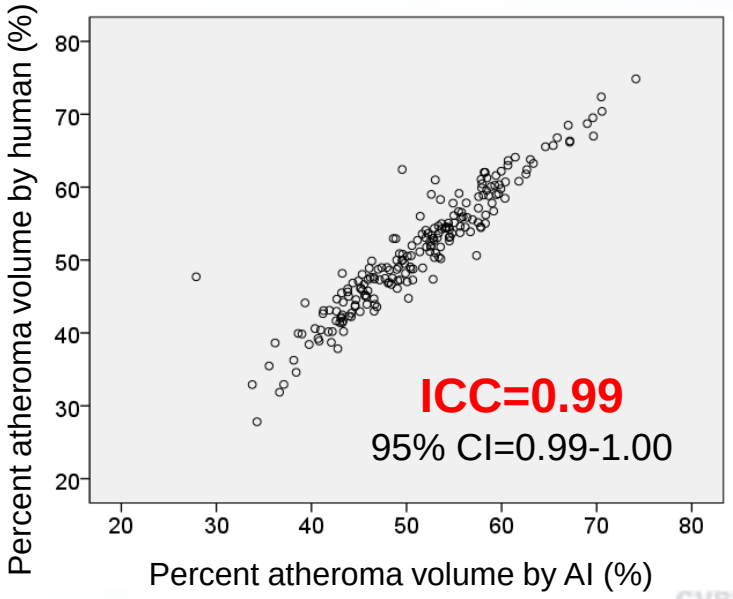


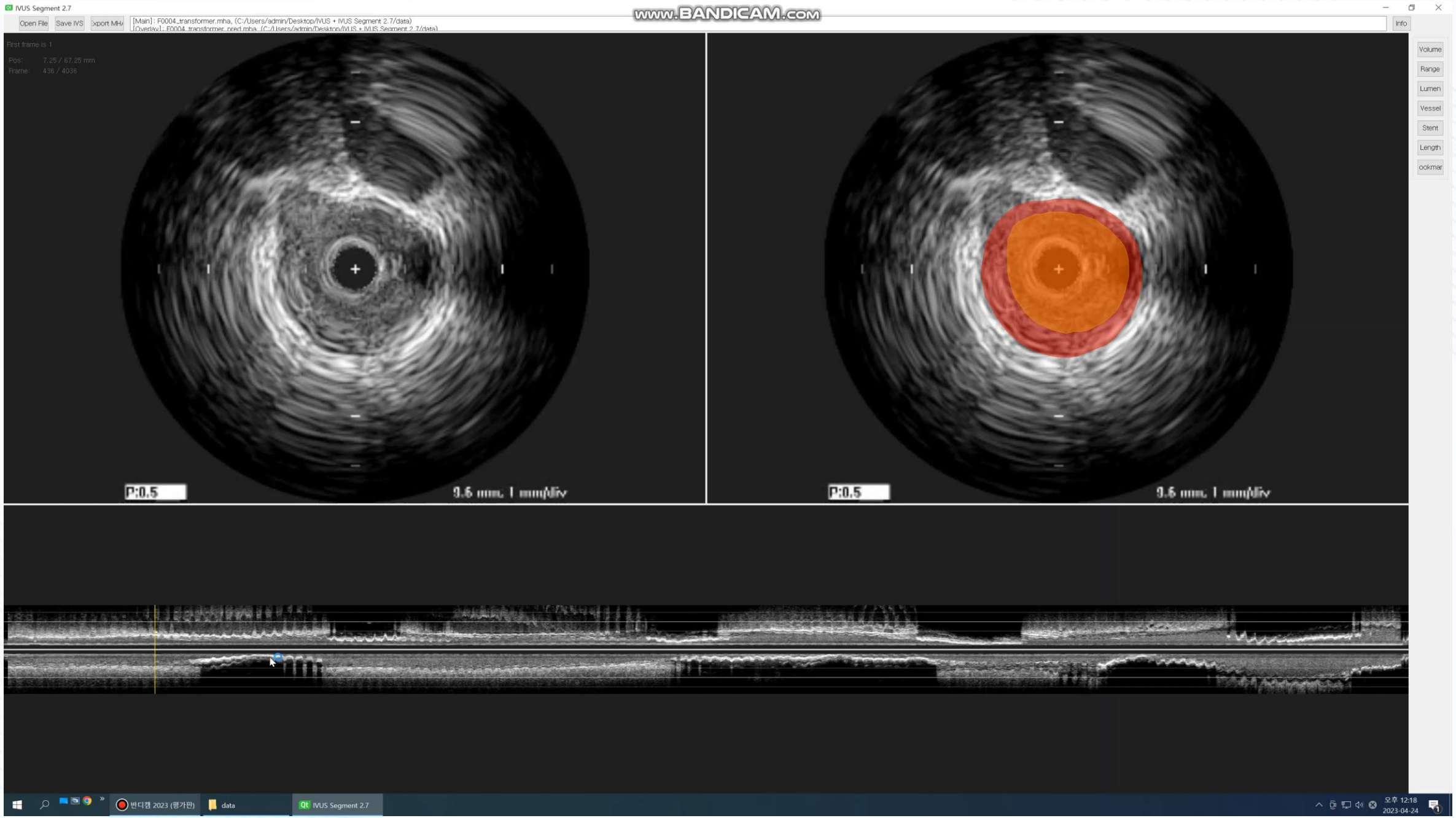


Volume

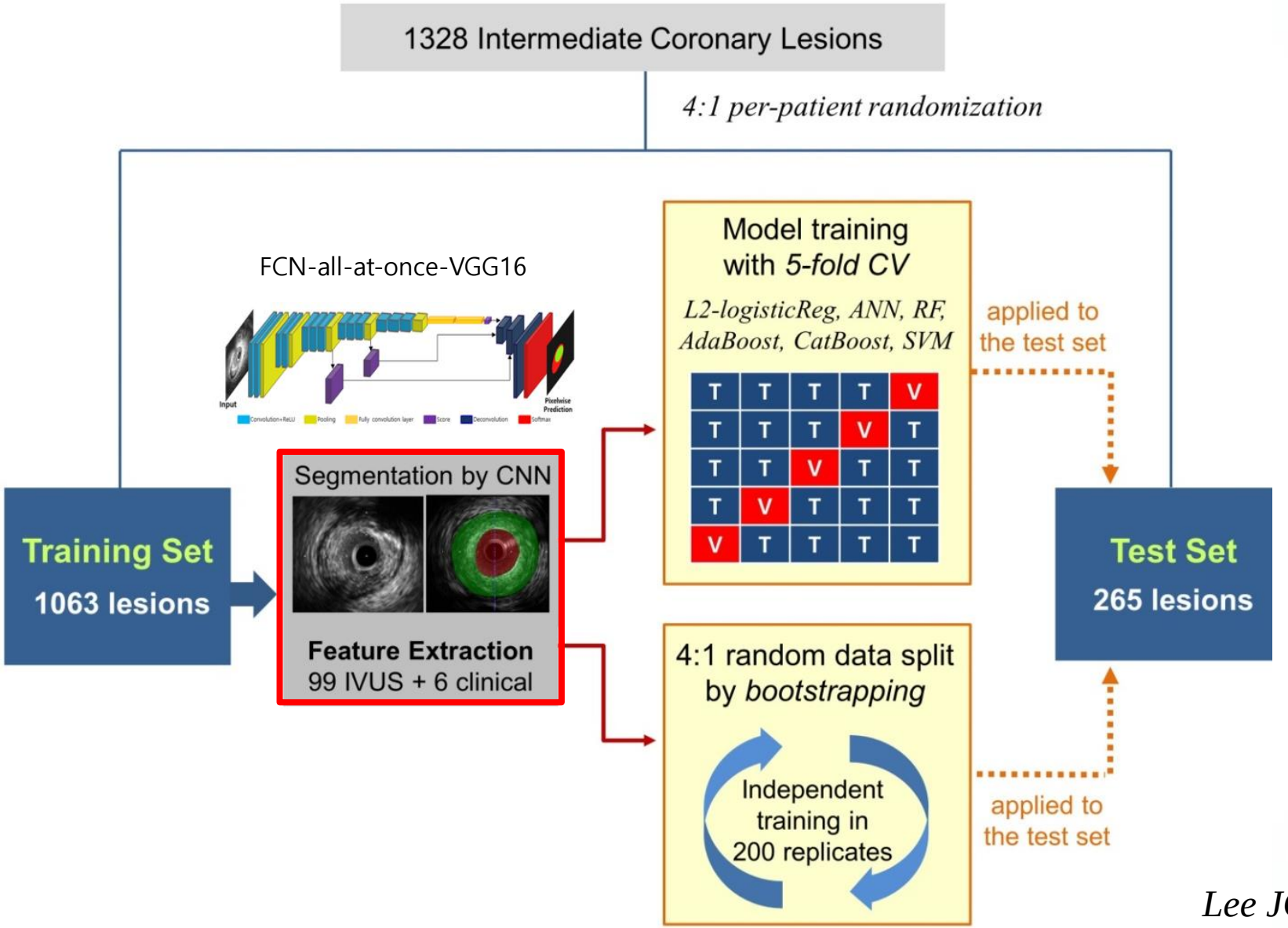








IVUS-Derived FFR by ML

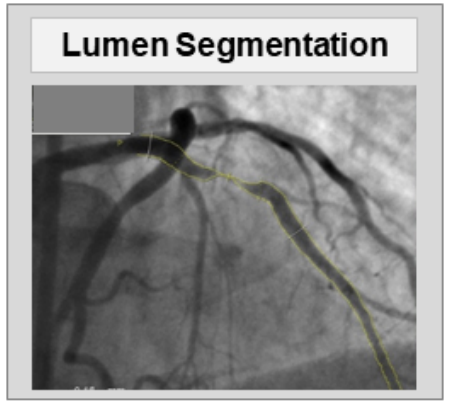


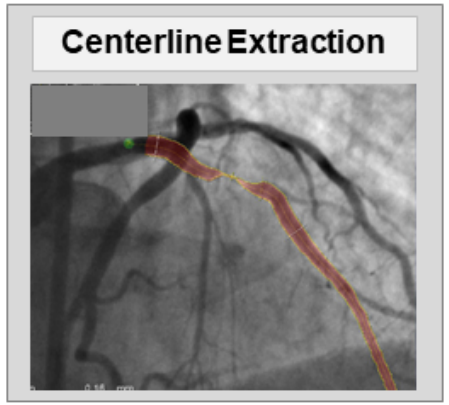
Prediction of FFR<0.80

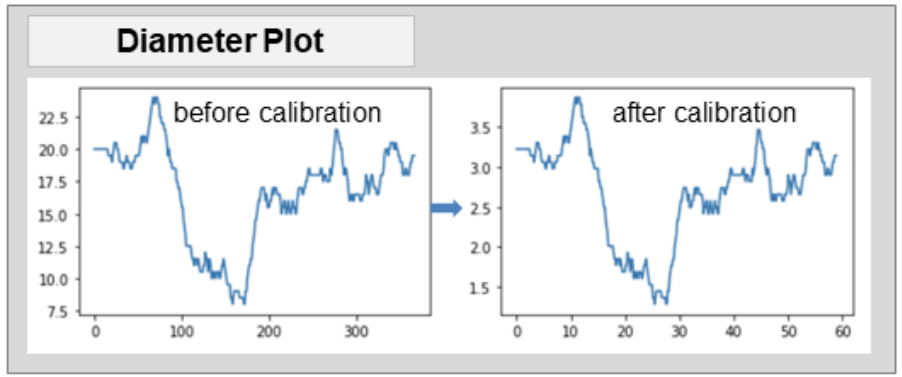
Test set	L_2-logistic regression	Random forest
AUC	0.87	0.85
sensitivity	70%	71%
specificity	86%	88%
PPV	70%	72%
NPV	87%	88%
accuracy	82%	83%

Lee JG et al. Atherosclerosis 2020;292:171-7

Angio-Derived FFR by ML







1501 Intermediate Coronary Lesions in 1501 Patients

Training: Test= 4:1 randomization

Feature Extraction
- 24 computed angiographic features on the diameter plot
- 4 clinical variables

Feature Selection
12 high-ranking features selected by scatter search
(segment, gender, length-D<1.25, distal lumen diameter, diameter within the worst, MLD, DS, BSA, length-D<2.0, distal 5-mm RLD, length-DS>70, length-D<1.5)

Training (N=1204)

XGBoost with all 28 features → parameter tuning with 5-fold CV

XGBoost with 12 features → final training

Test (N=297)

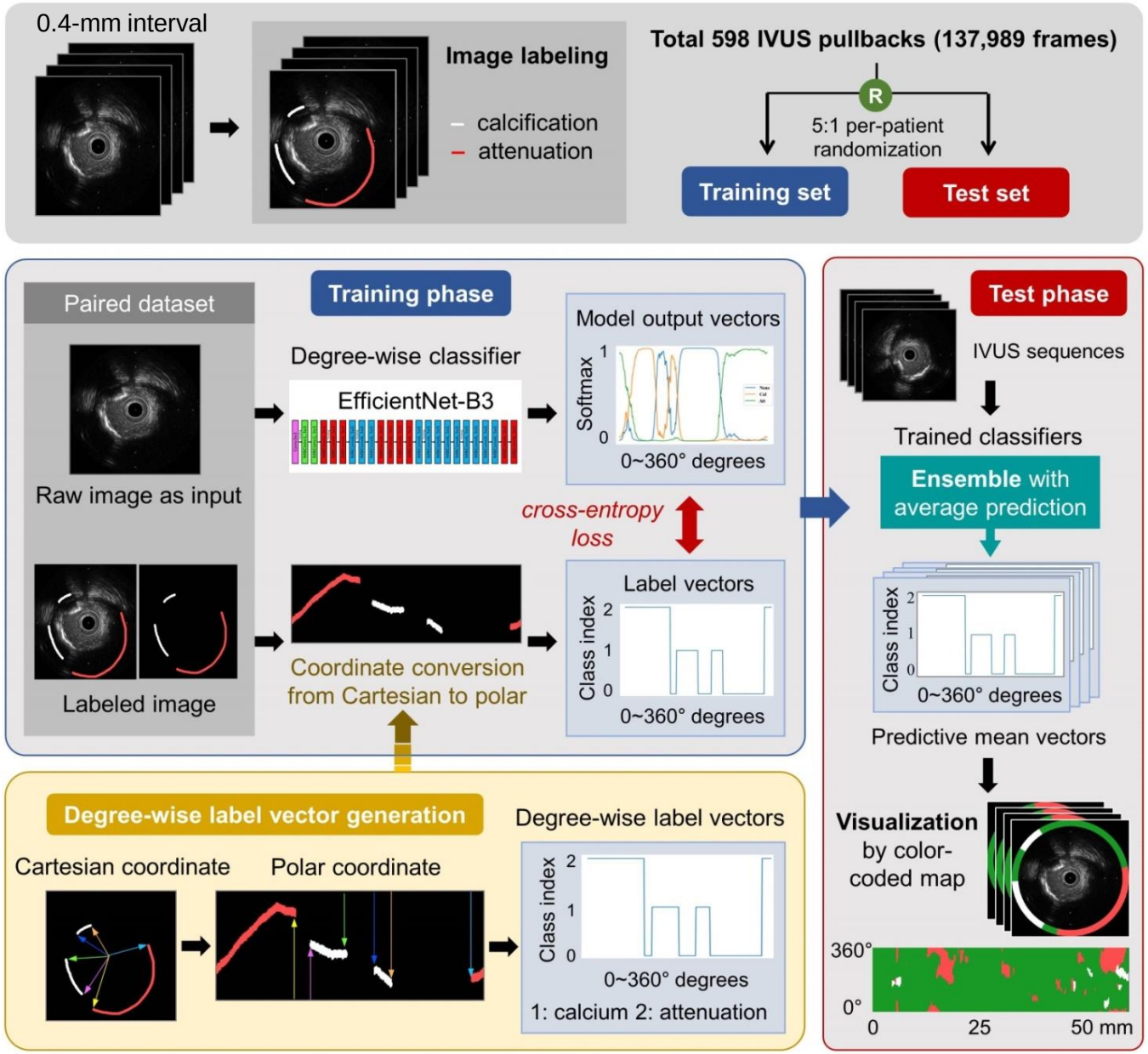
Trained XGBoost → Binary Classification FFR<0.80 vs. ≥0.80

Prediction of FFR<0.80

	Test	External
AUC	0.87	0.87
sensitivity	84%	80%
specificity	80%	87%
PPV	81%	74%
NPV	84%	90%
accuracy	82%	85%

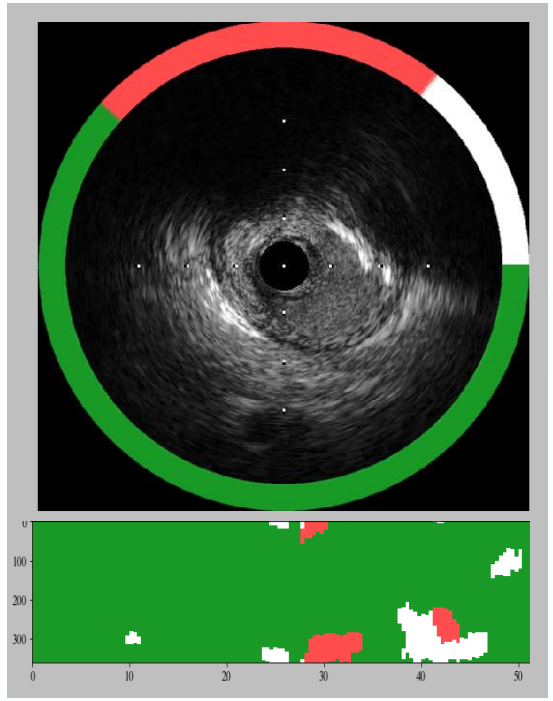
Cho et al. J Am Heart Assoc 2019;8:e011685
Hae et al. PLOS Medicine 2018;15:e1002693

DL for IVUS Plaque Characterization



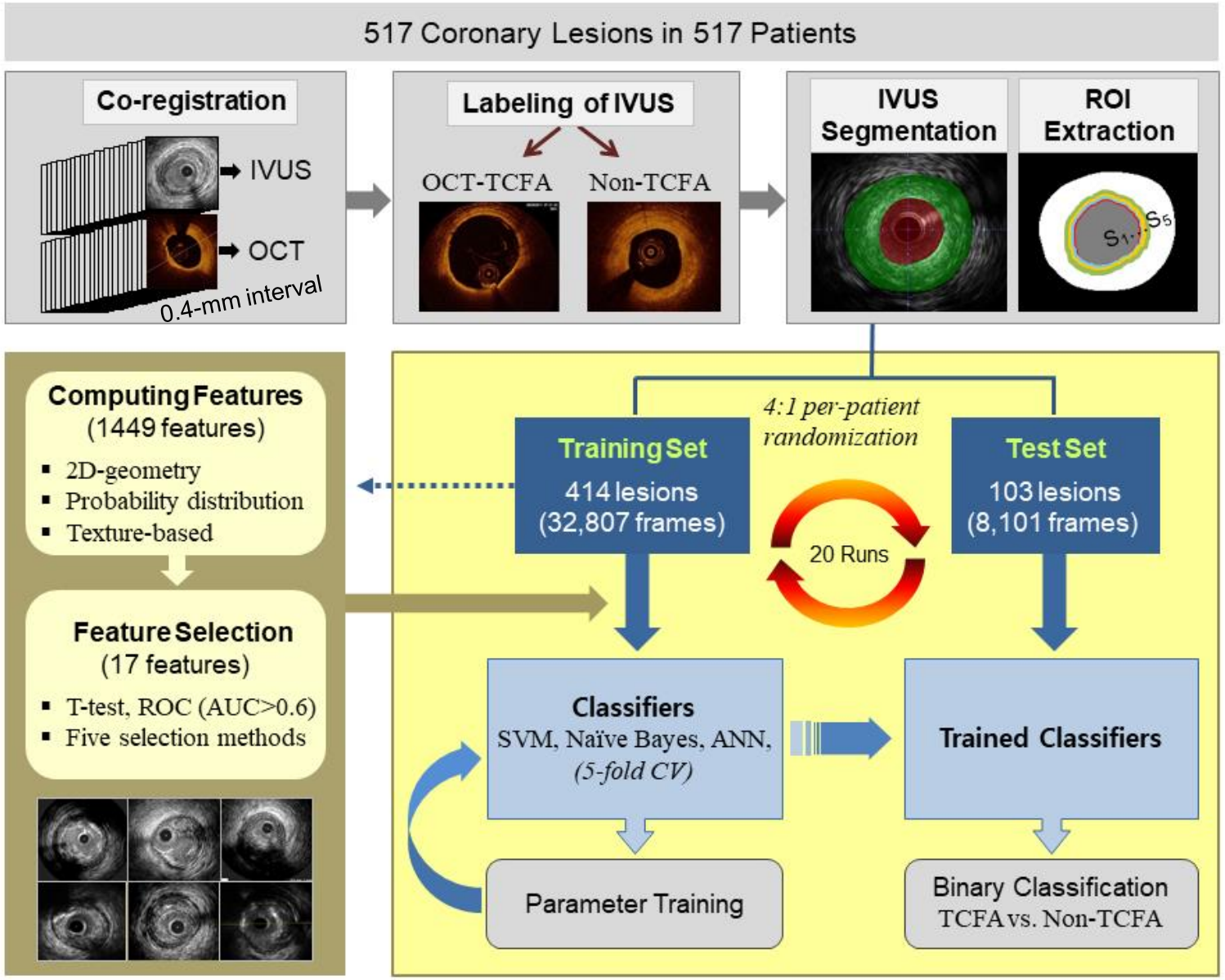
- Angle-level accuracy 98%
- Inference time/vessel 7.8 s

Frame-level	DSC	sensitivity	specificity	accuracy
calcification	0.84	86%	97%	96%
attenuation	0.80	80%	96%	93%



Cho et al. Atherosclerosis 2021;324:69-75

IVUS-Based TCFA Detection by ML



Frame-level performance to predict OCT-TCFA

Test set	SVM	Naïve Bayes	ANN
AUC	0.77	0.78	0.82
sensitivity	80%	80%	82%
specificity	71%	71%	80%
accuracy	78%	80%	82%

Bae et al. Atherosclerosis 2019;288:168-74

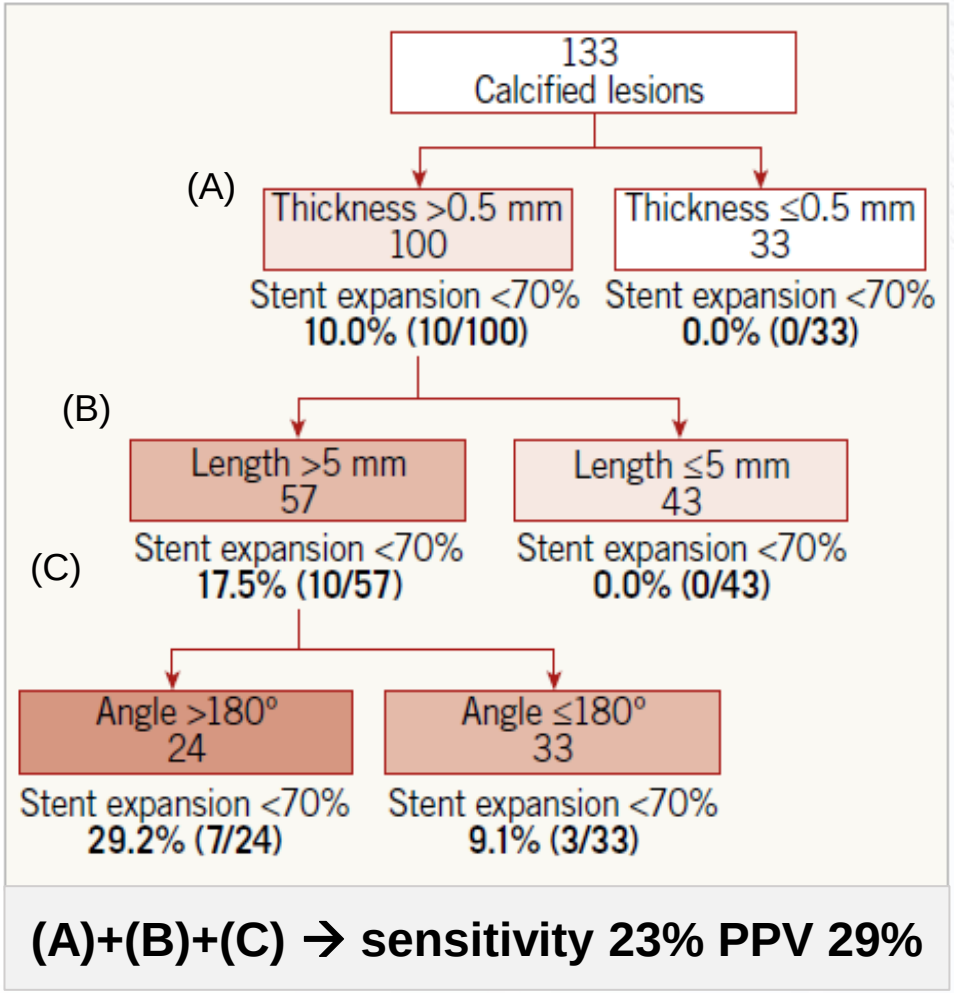
Pre-procedural Prediction of Stent Underexpansion

Multivariable linear regression model to predict stent expansion

Covariate	Regression coefficient	95% confidence interval	*p*-value
Maximum calcium angle (per 180°)	–7.43	–12.6 to –2.21	<0.01
Maximum calcium thickness (per 0.5 mm)	–3.40	–6.35 to –0.45	0.02
Calcium length (per 5 mm)	–2.32	–4.09 to –0.55	0.01

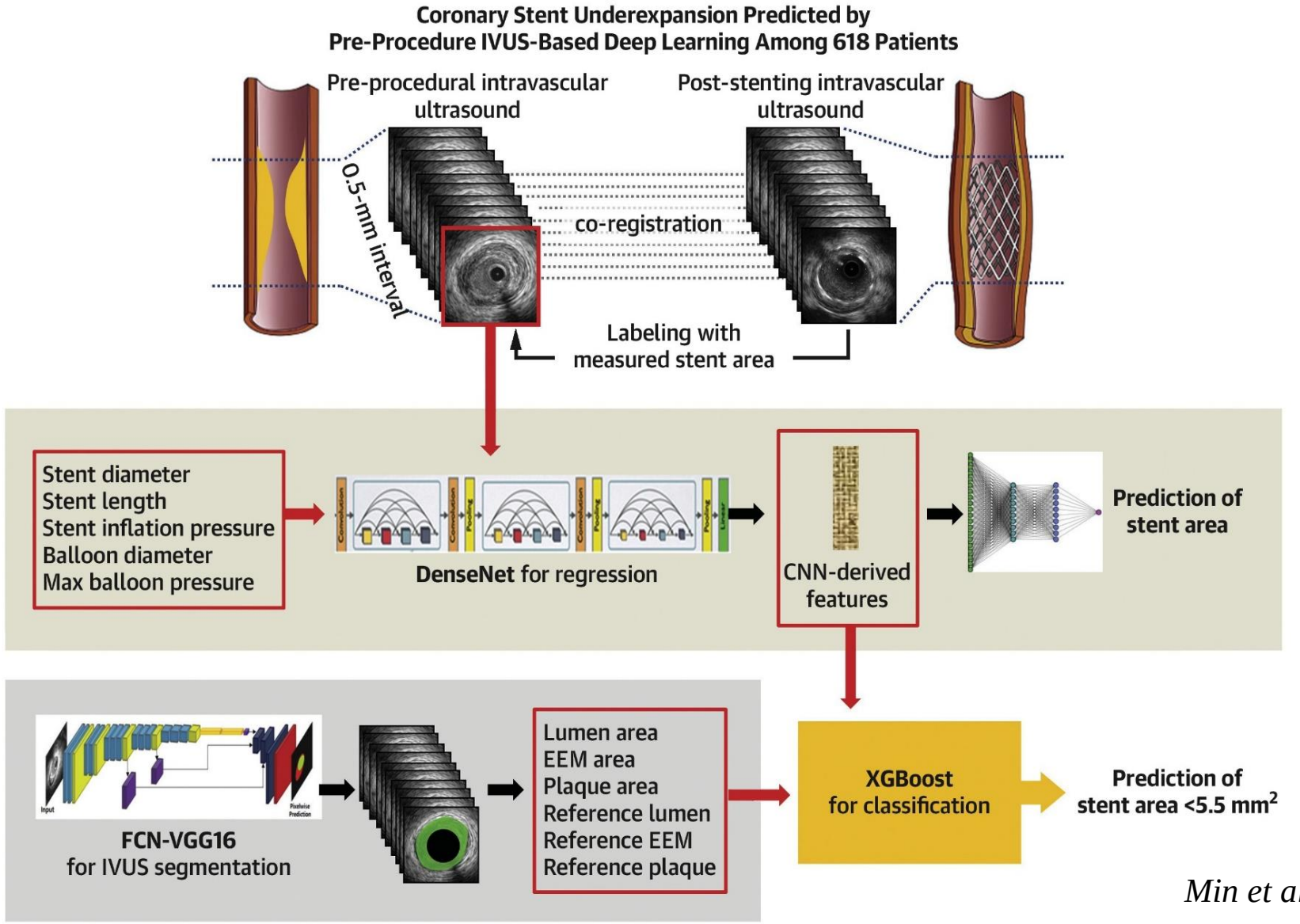
Fujino et al. Eurointervention 2018;13:e2182-9

To predict stent expansion <70%



(A)+(B)+(C) → sensitivity 23% PPV 29%

DL to Predict Stent Underexpansion



Frame-level performance to predict stent < 5.5mm^2

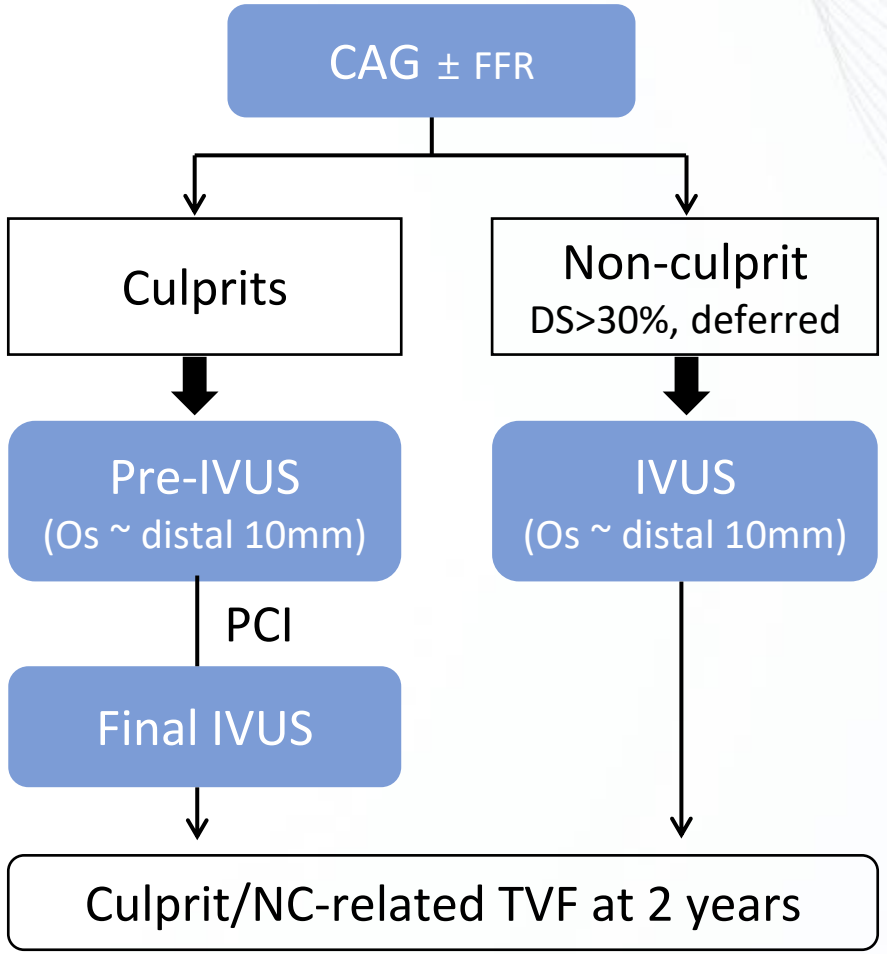
Test set	Sensitivity -Specificity Trade-off	Precision -Recall Trade-off
AUC	0.94	0.94
sensitivity	85%	63%
specificity	85%	96%
PPV	37%	63%
NPV	98%	96%
accuracy	85%	93%

Min et al. JACC Cardiovasc Interv 2021;14:1021-9

INNOVATE-PCI for Validation

INfluence of ***NO***vel Intra***V***ascular Ultrasound-Based ***A***rtificial Intelligence ***T***echnologies on ***E***vent Reduction Following ***P***ercutaneous ***C***oronary ***I***ntervention

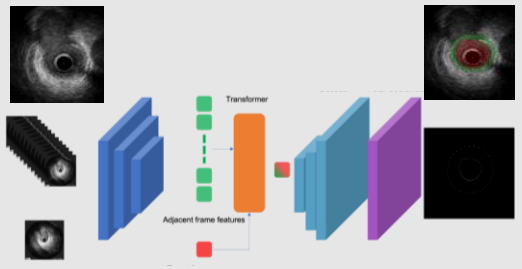
- 2020,8 - 2025,8
- Prospective multicenter registry
- 3000 pts. with IVUS-guided PCI
- To validate model performance & clinical impact
- Primary endpoint : 2-year TVF



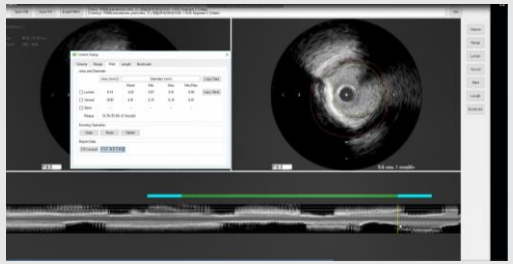
PI: Seung-Whan Lee, Asan Medical Center
Sponsor: Boston Scientific

2017 - 2022

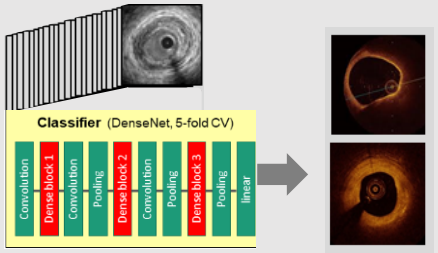
IVUS segmentation



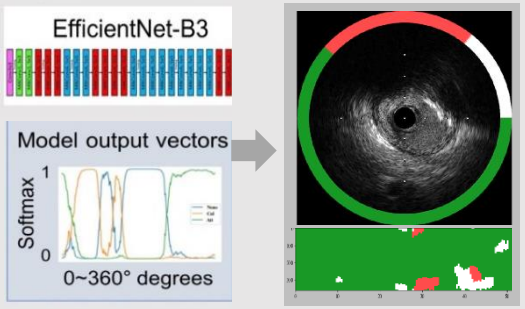
Automatic measurement



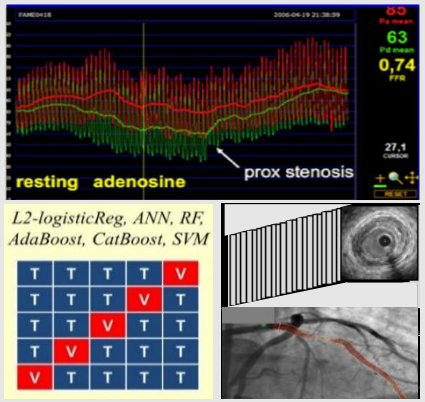
Detection of TCFA



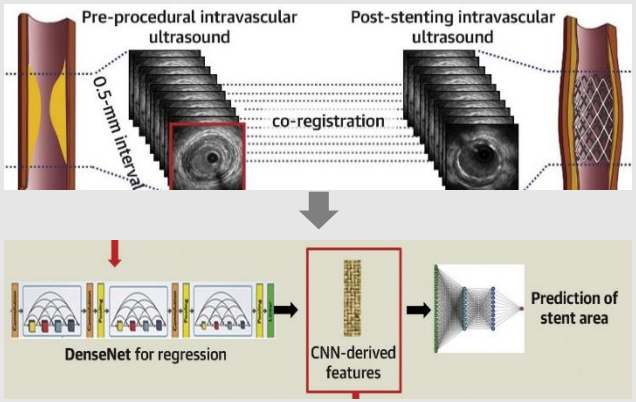
Plaque characterization



Prediction of FFR



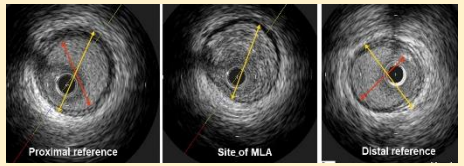
Prediction of underexpansion



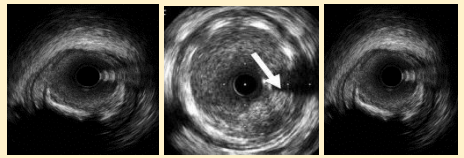
Segmentation by transformer

2023 - 2025

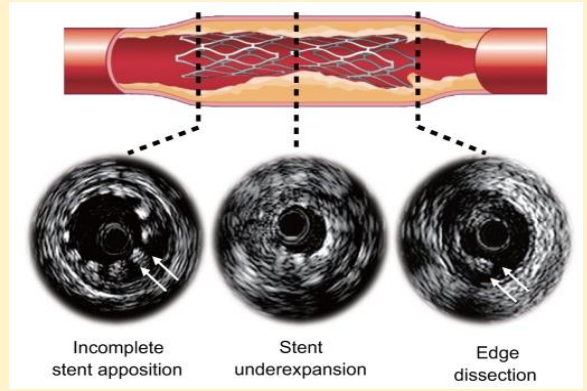
Stent sizing



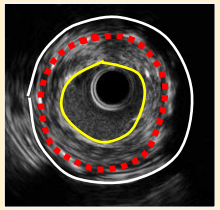
Acute complication



Stent optimization



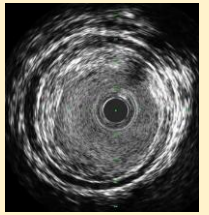
Segmentation for stented lesions



Application to complex lesions

- left main
- bifurcation
- CTO
- in-stent restenosis

Tuning for HD-IVUS



UI/UX

Feasibility

Prospective, multi-center validation