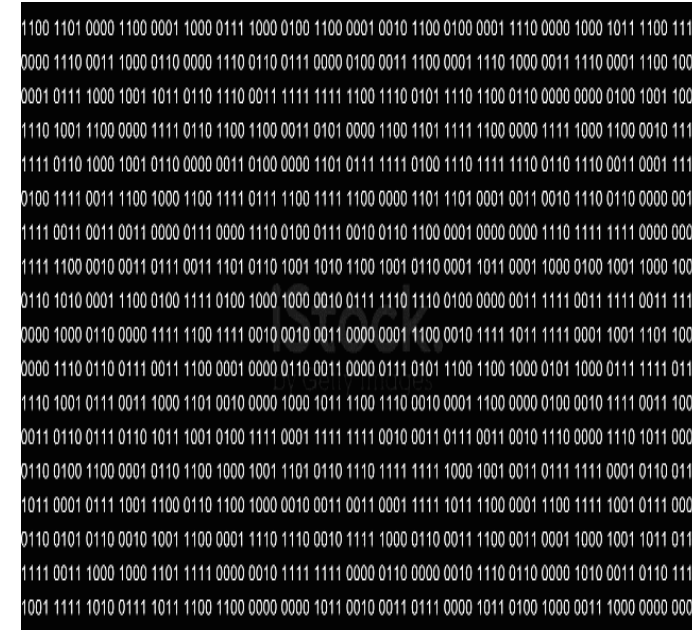
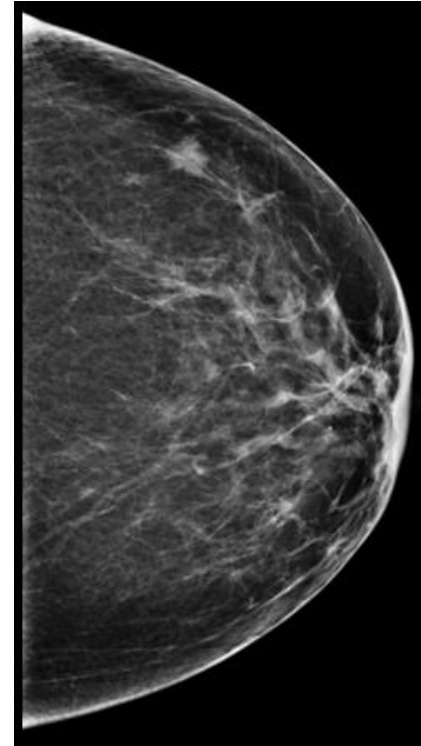
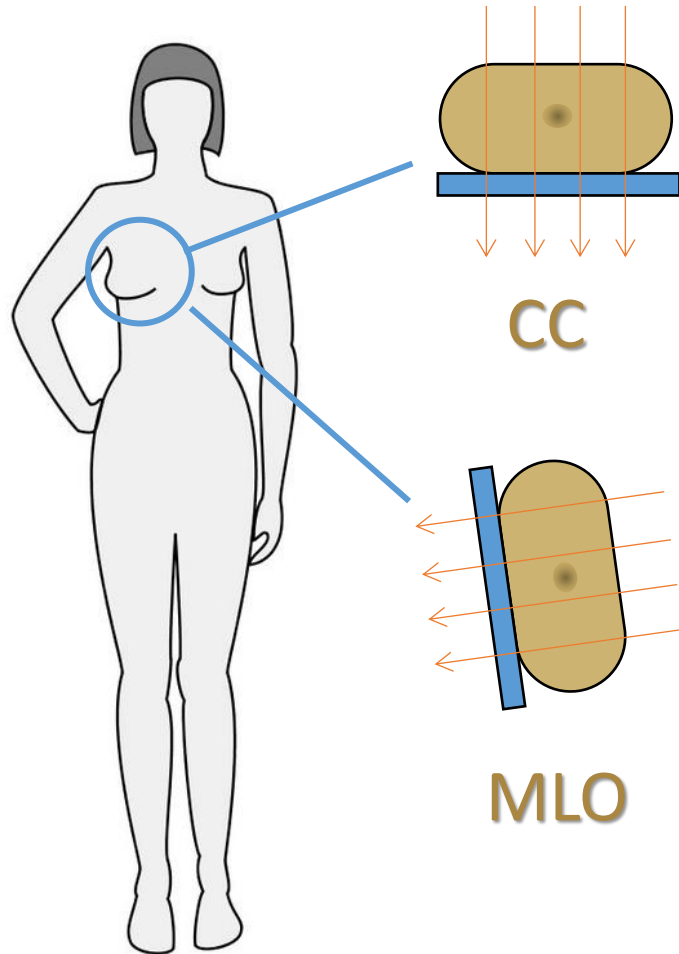


AI for Digital breast Tomosynthesis



Prof. Giovanni Mettivier



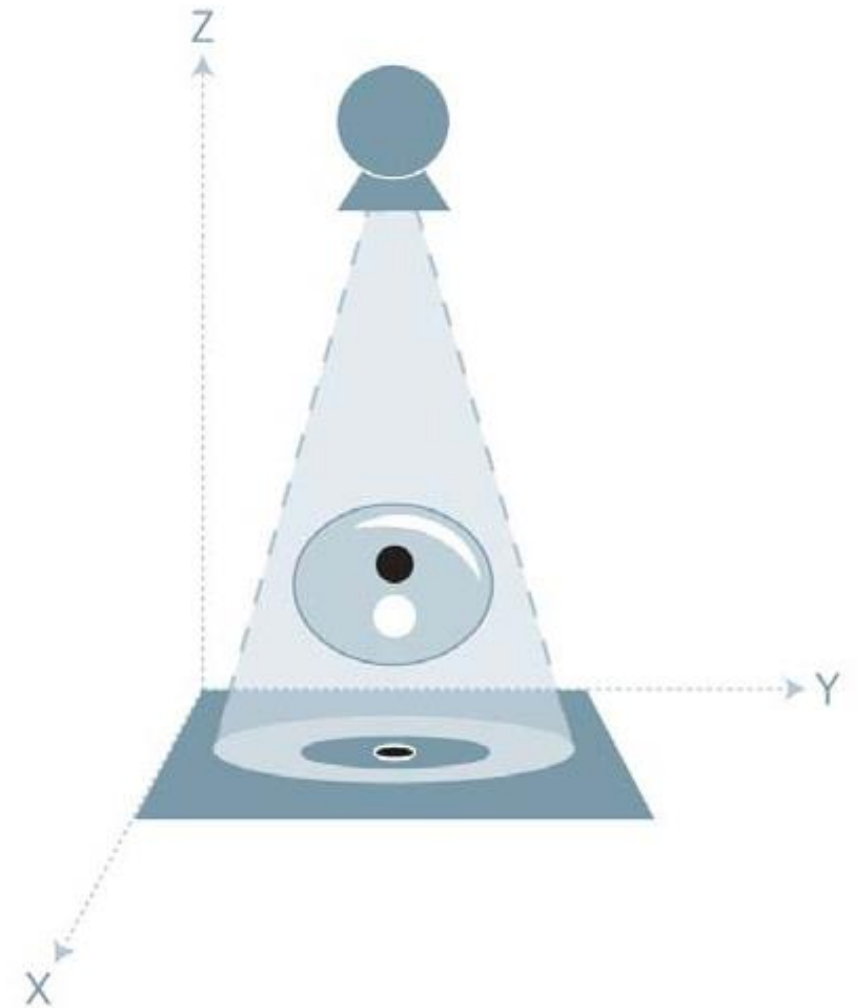
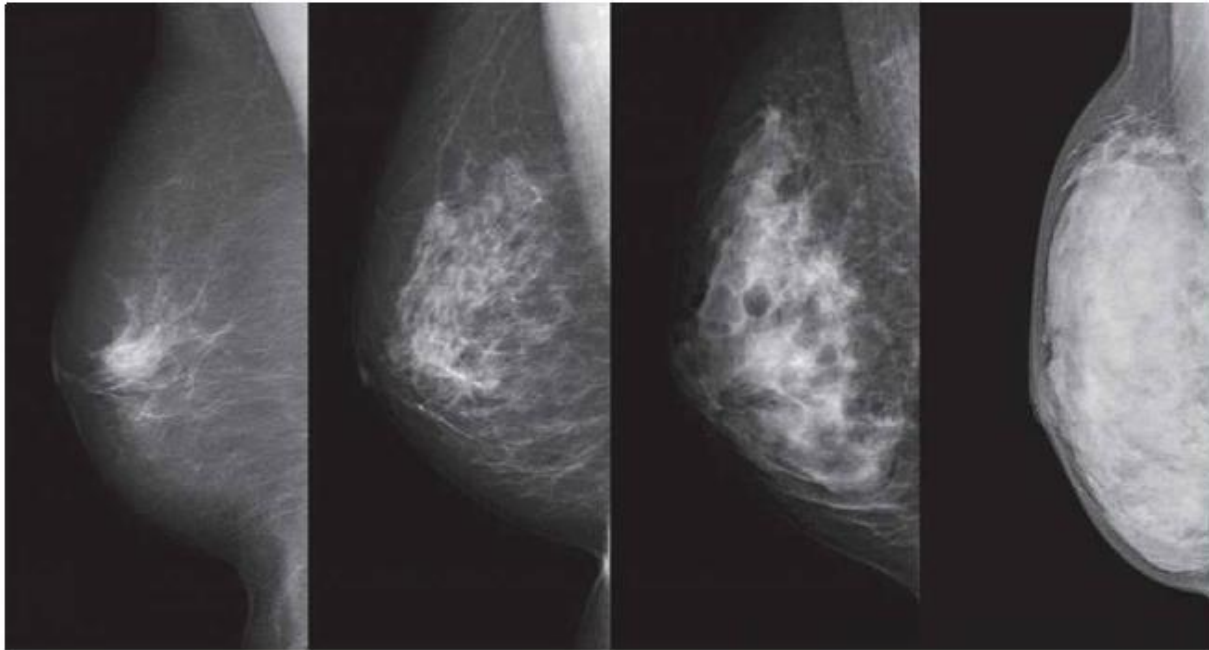
CC



MLO

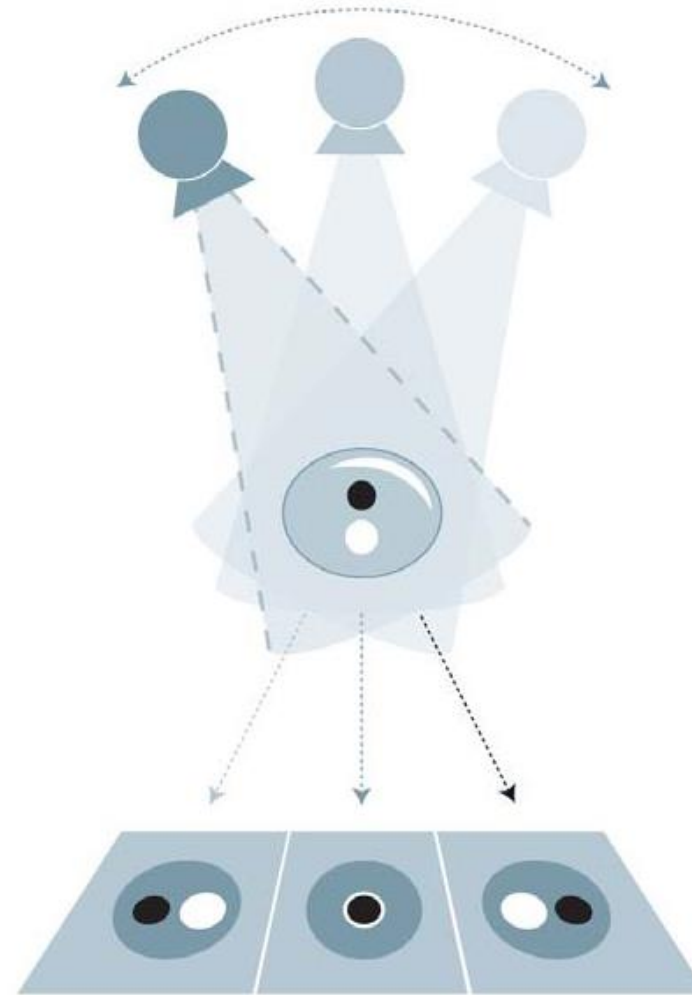
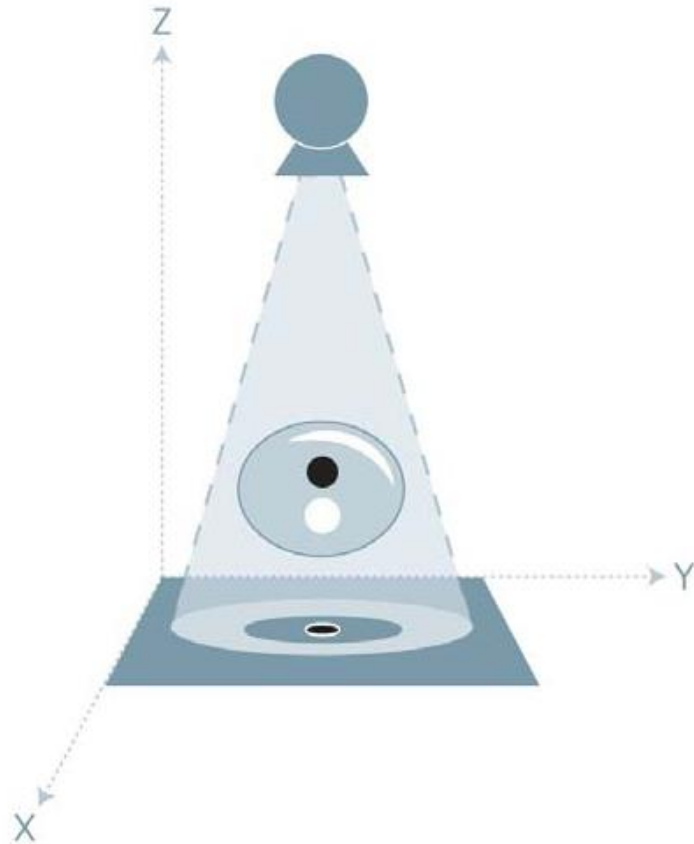
“However, due to the two-dimensional nature of projection imaging, mammography is limited by overlapping tissue

90%/10% ——— Fat - Glandular tissues ———> 10%/90%

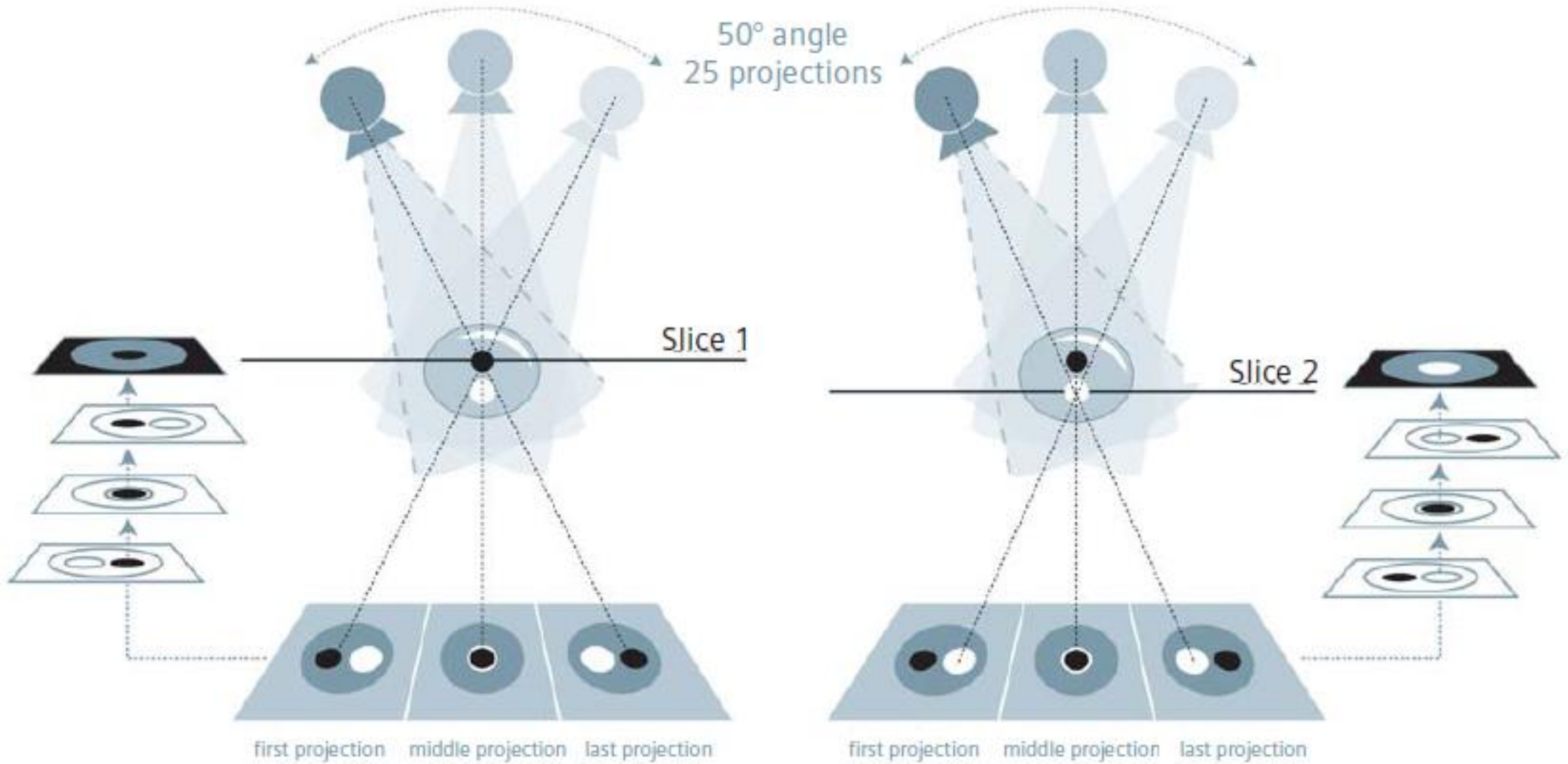


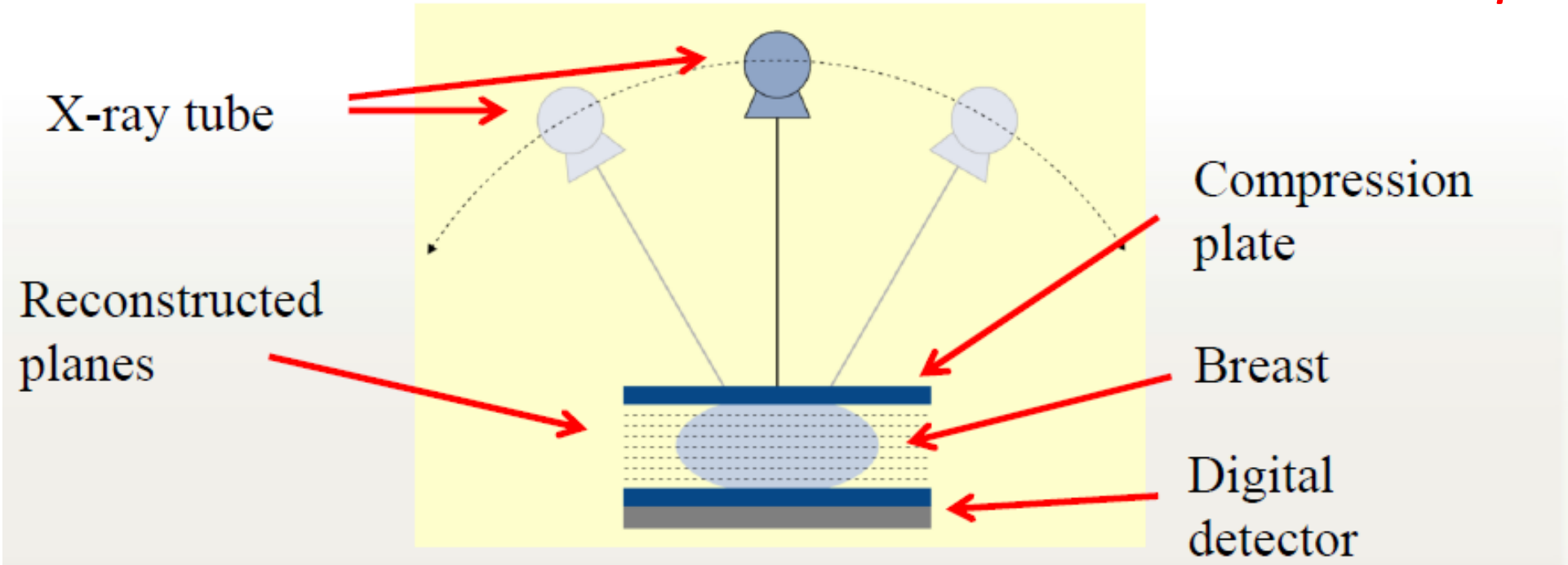
J. Baker & J. Lo, Duke University in Durham, NC, USA

A. Hebecker, T. Mertelmeier & J. Orman, Siemens Medical Solutions, Erlangen, Germany



www.siemens.com/healthcare

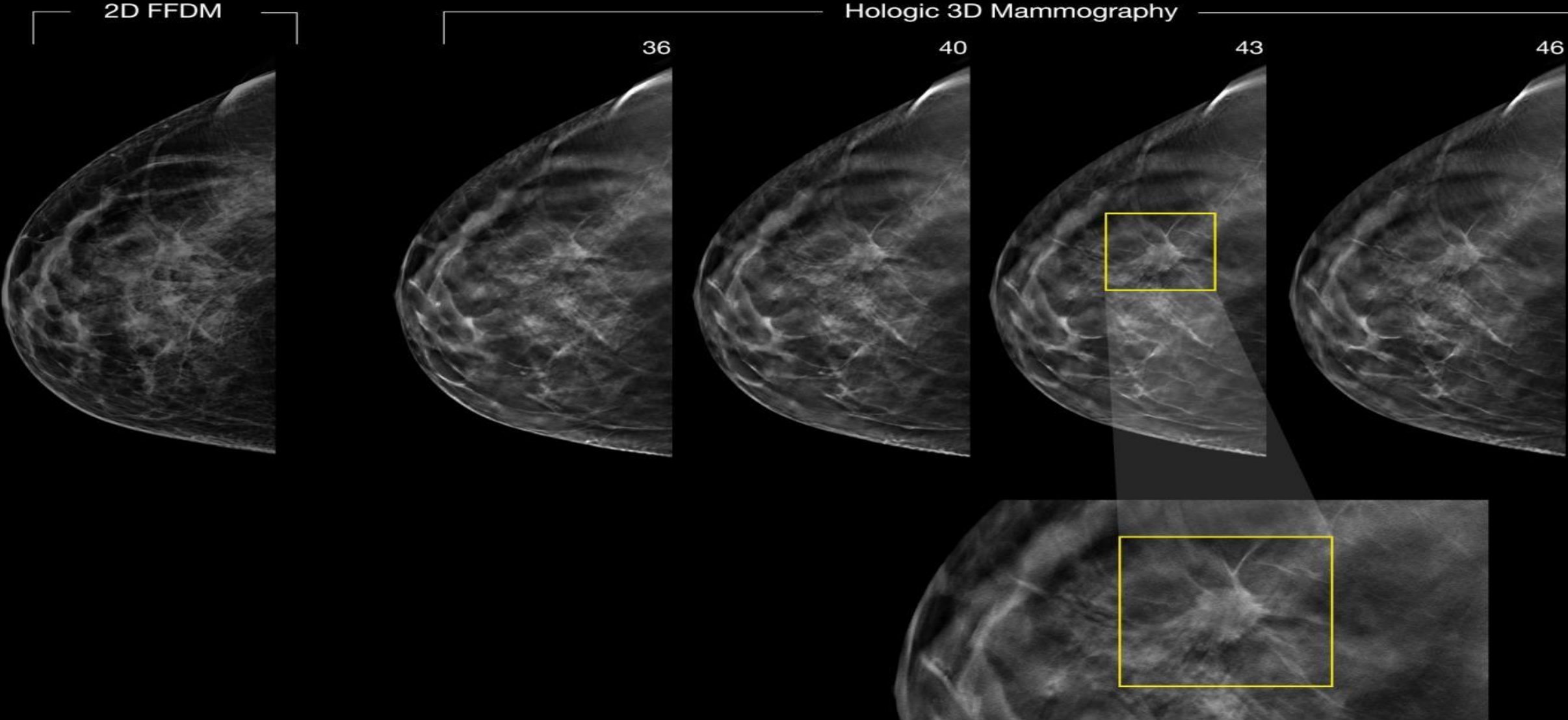


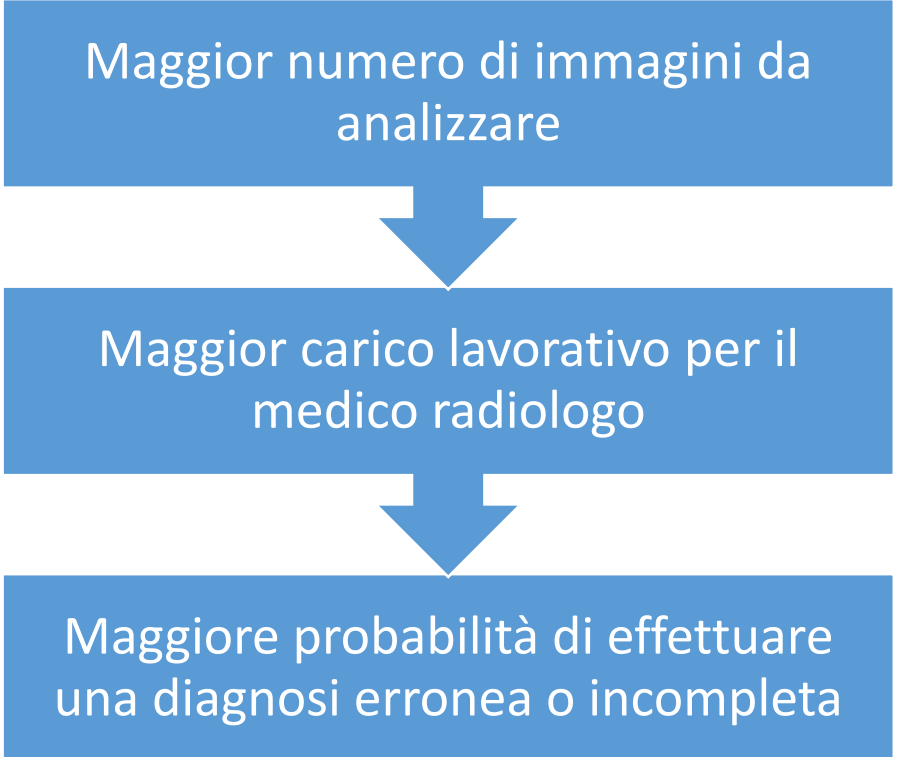
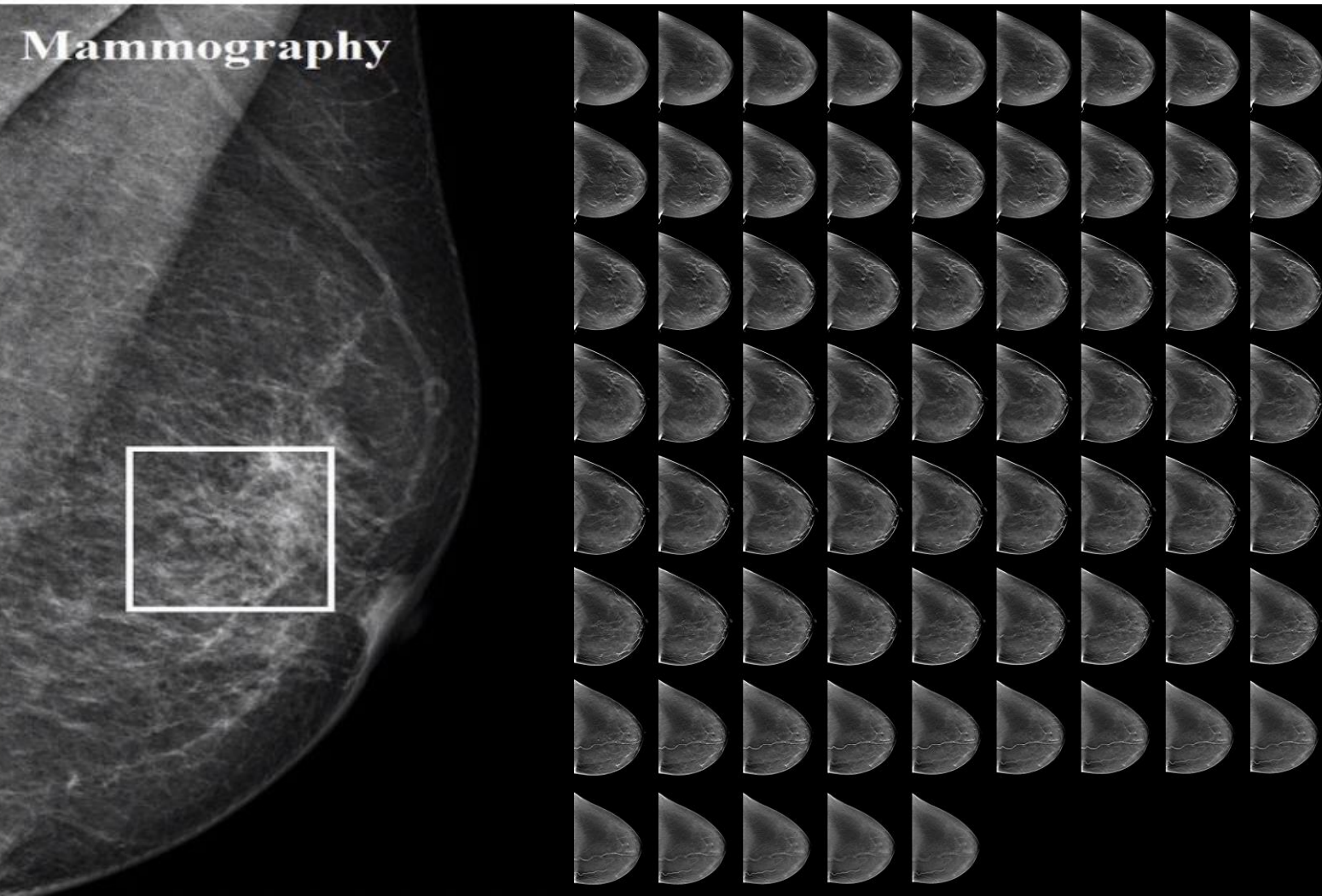


- X-ray tube moves in an arc across the breast
- Series of low dose images are acquired at different angles
- Total dose similar to single view breast exam

A. Smith, www.hologic.com

**A malignancy easily missed with conventional 2D mammography
was clearly seen with Hologic 3D Mammography**



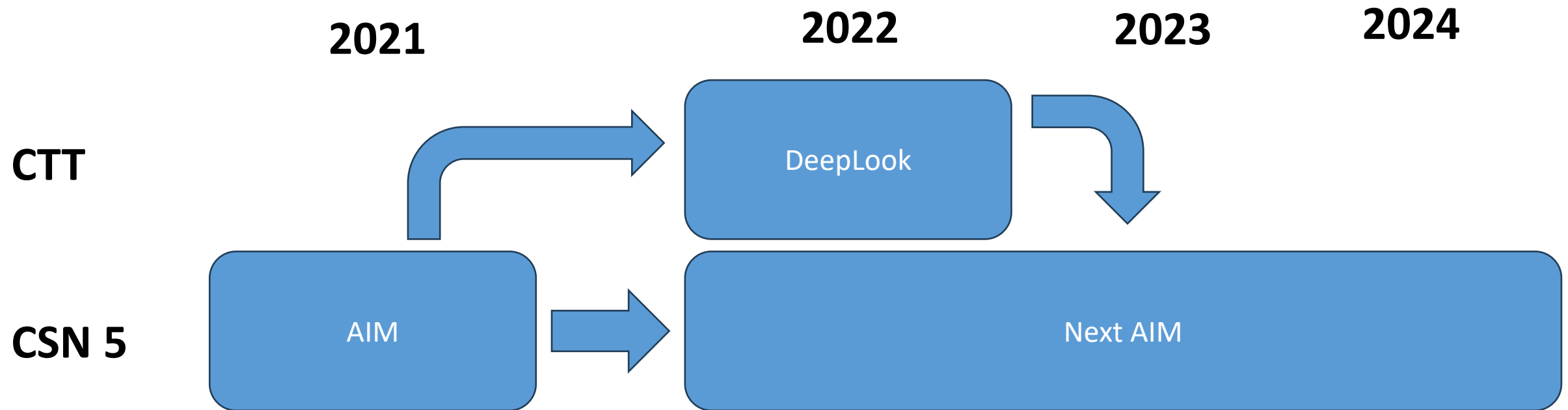




McDonald RJ et al, "The effects of changes in utilization and technological advancements of cross-sectional imaging on radiologist workload." Acad Radiol. Sep;22(9):1191-8 (2015).

DeepLook is a national Technological Transfer project founded by INFN and started in 2022.

The aim is to implement a deep learning architecture for Computed Aided Detection (CAD), based on neural networks developed with deep learning methods, for the automatic detection and classification of breast lesions in DBT images.





INFN Napoli

G. Mettivier, R. Ricciardi, D. Esposito, P. Russo, M. Staffa, S. Clemente

INFN Bologna

D. Remondini and Nico Curti



INFN Ferrata

G. Paternò



ASL CUNEO 1

M. Porzio

AORN Cardarelli

S. Minelli, E. Antignani, A. Santoro



IFO Regina Elena

V. Landoni, P. Ordonez, F. Ferranti, L. Greco, M. Masi



ALMA MATER STUDIORUM
UNIVERSITÀ DI BOLOGNA



Dataset (Hospital site)	Expected final no. of patients	Present no. of patients	Total no. DBT slices	TP	TN	Bio	DBT scanner	View	FFDM available
AORN Cardarelli	250	200	7466	3528	3938	Yes	Giotto Class 40000	CC, MLO	Yes
IRCSS R. E.	250	96	2915	1541	1374	Yes	Giotto Class 40000	MLO	No
ASL Cuneo 1	500	10	-	-	-	Yes	Multi	CC, MLO	
AOU Fed II	250	-	-	-	-	No	Hologic Selenia Dimensions	CC, MLO	Yes
Duke	349	349	21518	14057	7461				



All the images were annotated by dedicated breast radiologists

Duke Dataset

Custom dataset of digital breast tomosynthesis (DBT) from Duke University Hospital

Exclusion criteria:

- Presence of breast implants
- Presence of metal objects
- Presence of image artifacts

30 NEGATIVE patients

120 DBT volumes

- 30 RCC
- 30 LCC
- 30 LMLO
- 30 RMLO

Total of images: 7888

Selection of 20 images for DBT volume

Step* = Volume size/20

* rounded to the nearest integer

Final selected images of negative patients: 2400

35 BENIGN tumor patients

60 DBT volumes

- 15 LCC
- 15 RCC
- 15 LMLO
- 15 RMLO

Total of images: 4033

35 MALIGNANT tumor patients:

60 DBT volumes

- 15 LCC
- 15 RCC
- 15 LMLO
- 15 RMLO

Total of images: 4134

70 POSITIVE patients

120 DBT volumes

Total of images: 8167

Selection of images containing the lesion:
central image +/- 25% of the volume size*

*According to the information provided with the
dataset description

Selected images of positive patients: 2232

Selection of 20 images for volume (if available)

Step* = Volume size/20

* rounded to the nearest integer

Final selected images of positive patients: 2045

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Original Investigation | Health Informatics

August 16, 2021

A Data Set and Deep Learning Algorithm for the Detection of Masses and Architectural Distortions in Digital Breast Tomosynthesis Images

Mateusz Buda, MSc¹; Ashirbani Saha, PhD¹; Ruth Walsh, MD¹; et al

Author Affiliations | Article Information

JAMA Netw Open. 2021;4(8):e2119100. doi:10.1001/jamanetworkopen.2021.19100

Cornell University

We gratefully acknowledge support from the Simons Foundation, member institutions, and all contributors. [Donate](#)

arXiv > eess > arXiv:2011.07995

Electrical Engineering and Systems Science > Image and Video Processing

[Submitted on 13 Nov 2020 (v1), last revised 20 Nov 2022 (this version, v4)]

Detection of masses and architectural distortions in digital breast tomosynthesis: a publicly available dataset of 5,060 patients and a deep learning model

Mateusz Buda, Ashirbani Saha, Ruth Walsh, Sujata Ghate, Nianyi Li, Albert Świącicki, Joseph Y. Lo, Maciej A. Mazurowski

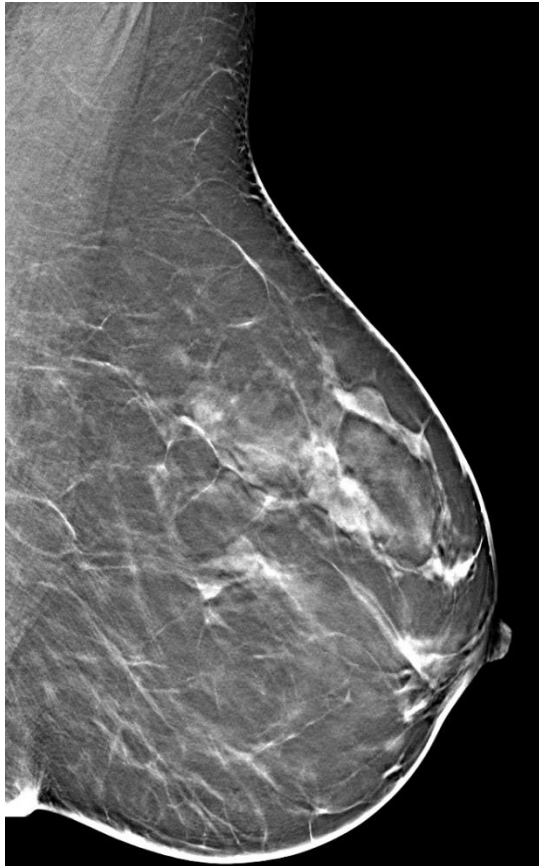
Breast cancer screening is one of the most common radiological tasks with over 39 million exams performed each year. While breast cancer screening has been one of the most studied medical imaging applications of artificial intelligence, the development and evaluation of the algorithms are hindered due to the lack of well-annotated large-scale publicly available datasets. This is

Step 1

Image
Pre-processing

Importantissimo il lavoro fatto con le GradCAM

PRIMA



Step 1

Riduzione del rumore

Step 2

Incremento del contrasto

Step 3

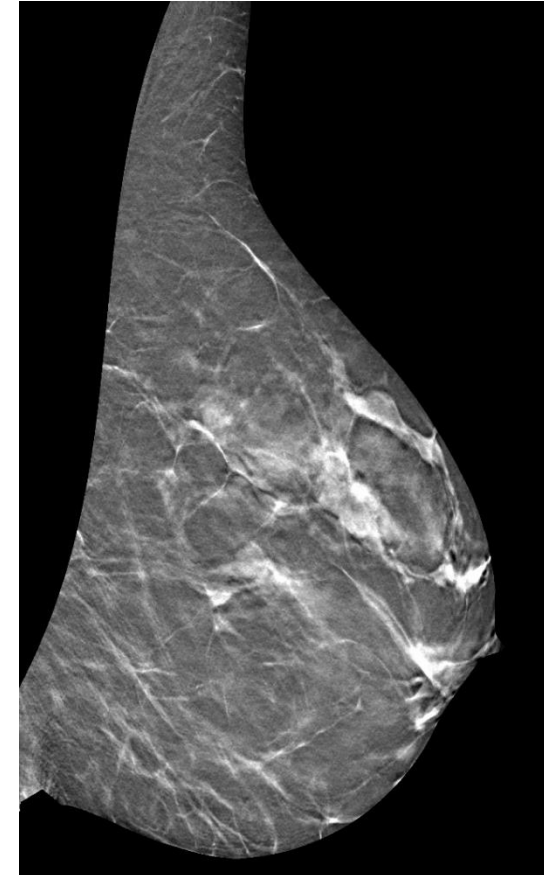
Eliminazione automatica:

- della pelle
- del capezzolo
- di ulteriori artefatti
- del muscolo pettorale ove presente (MLO vista)

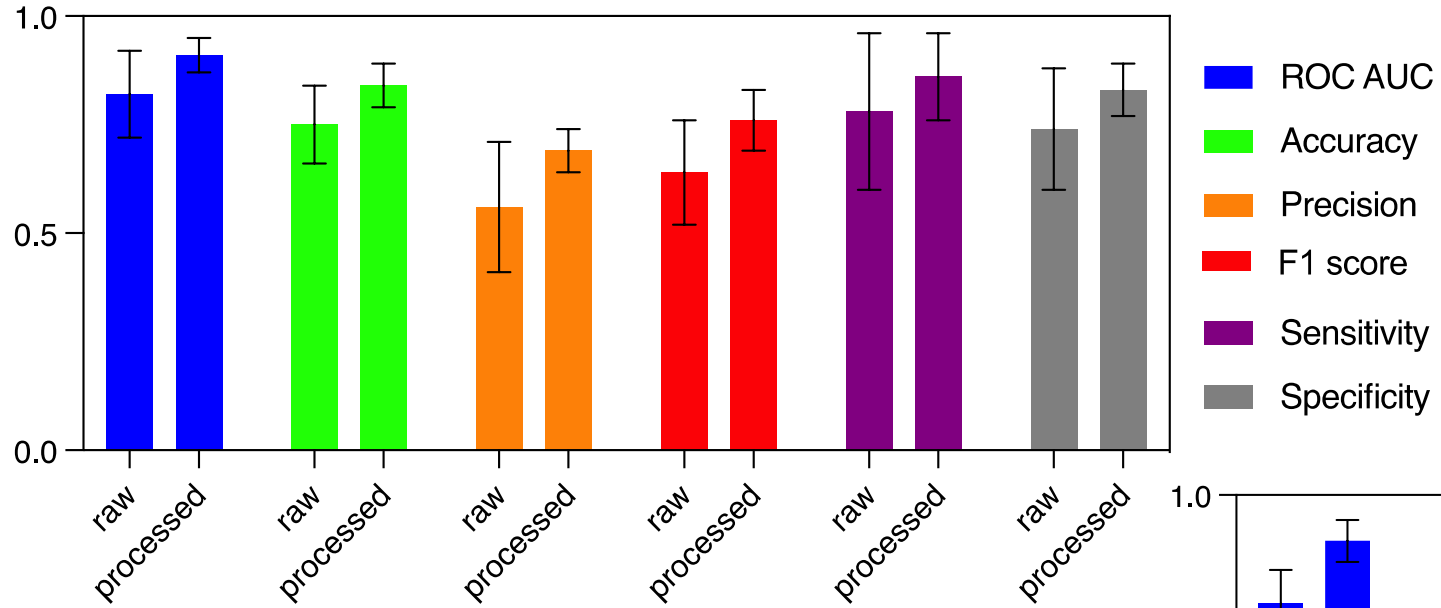
Step 4

Binning automatico delle slices a 300 x 300 px

DOPO

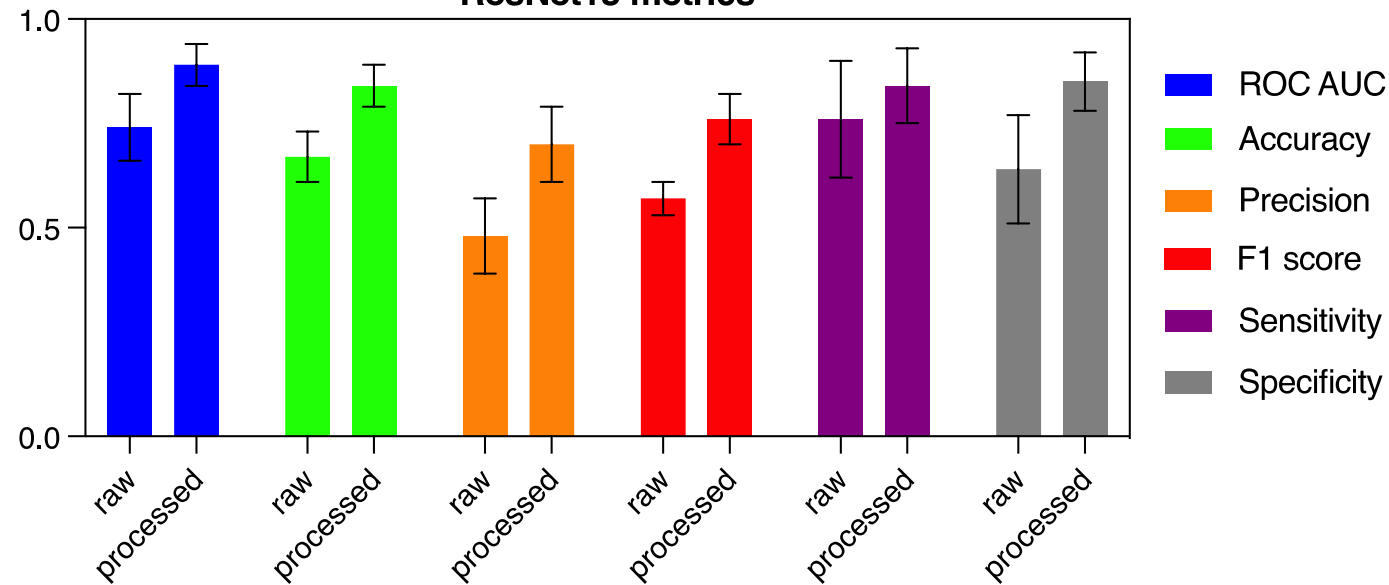


VGG16 metrics



Duke Dataset

ResNet18 metrics



Step 1

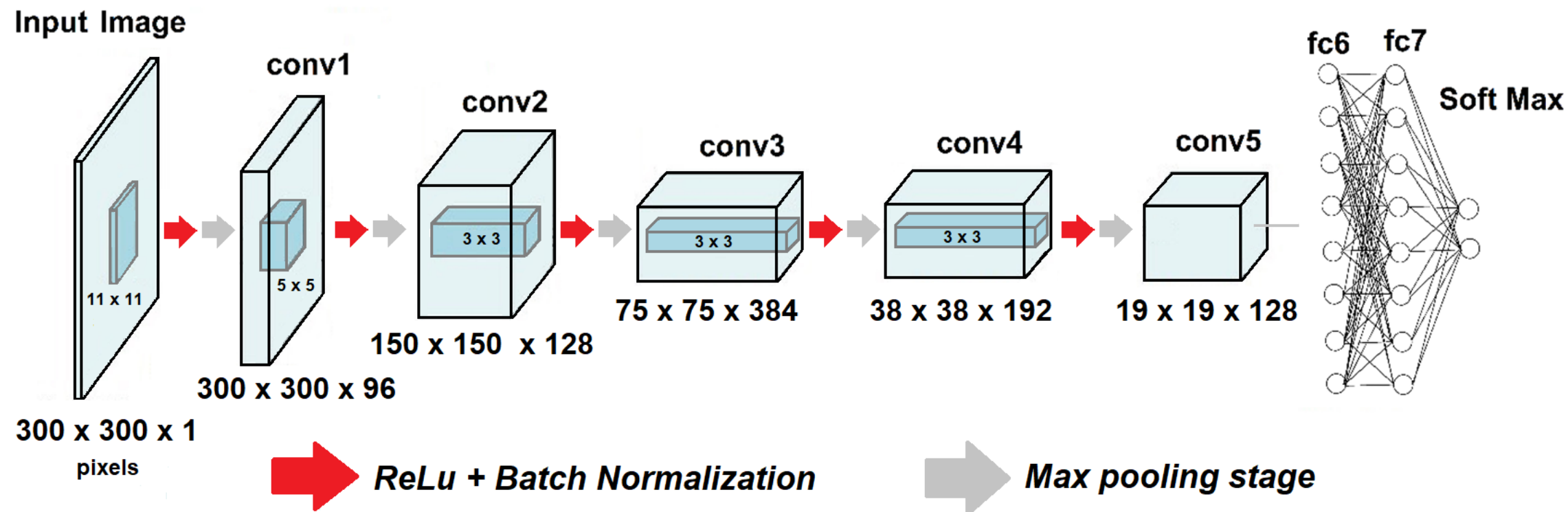
Image
Pre-processing



Step 2

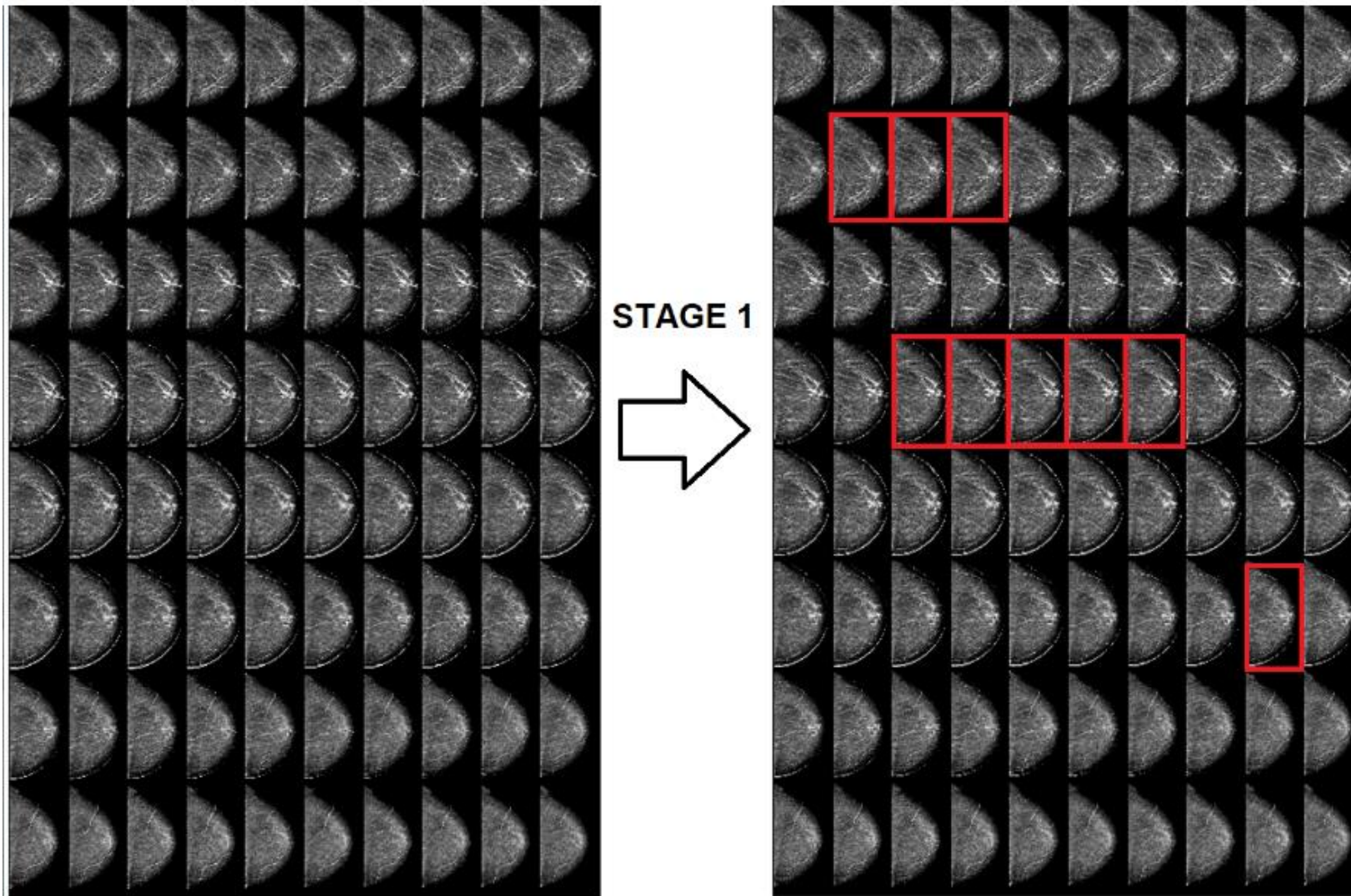
Slice
selection

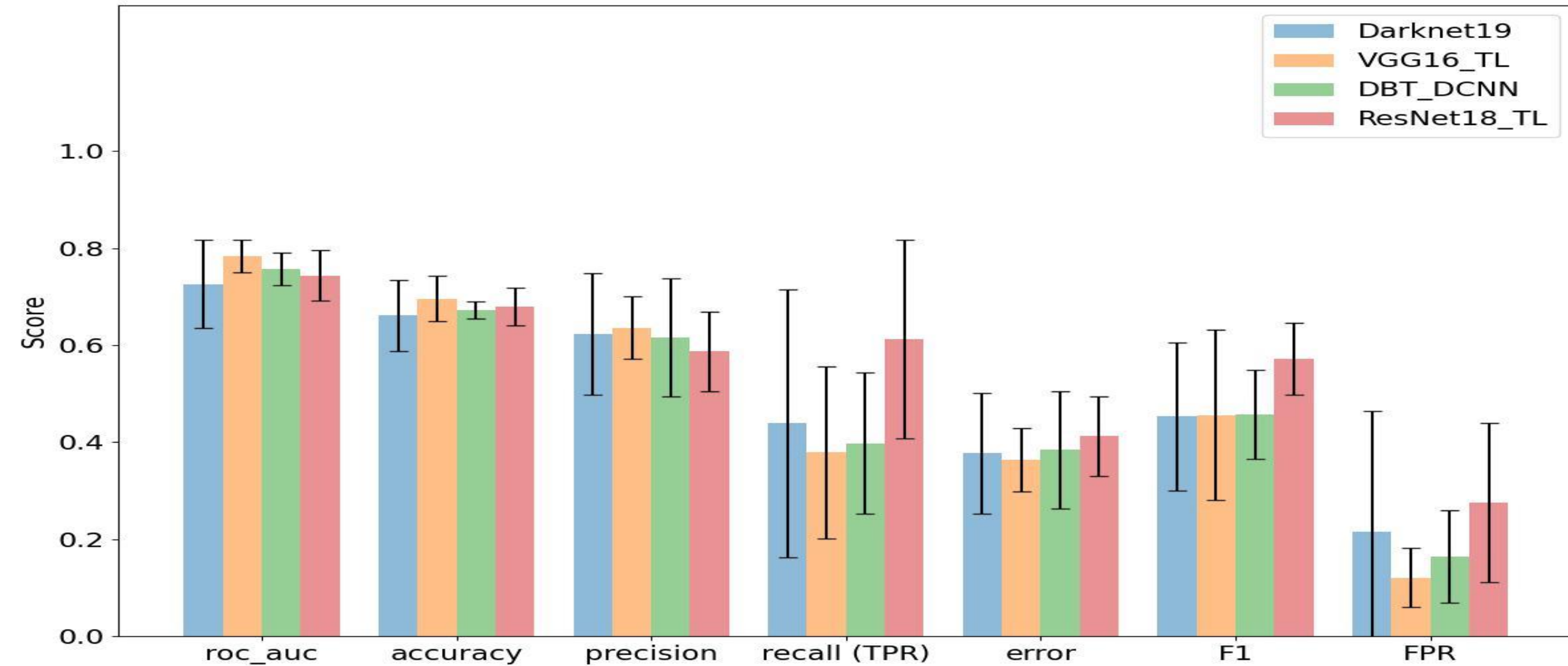
Slice selection - network

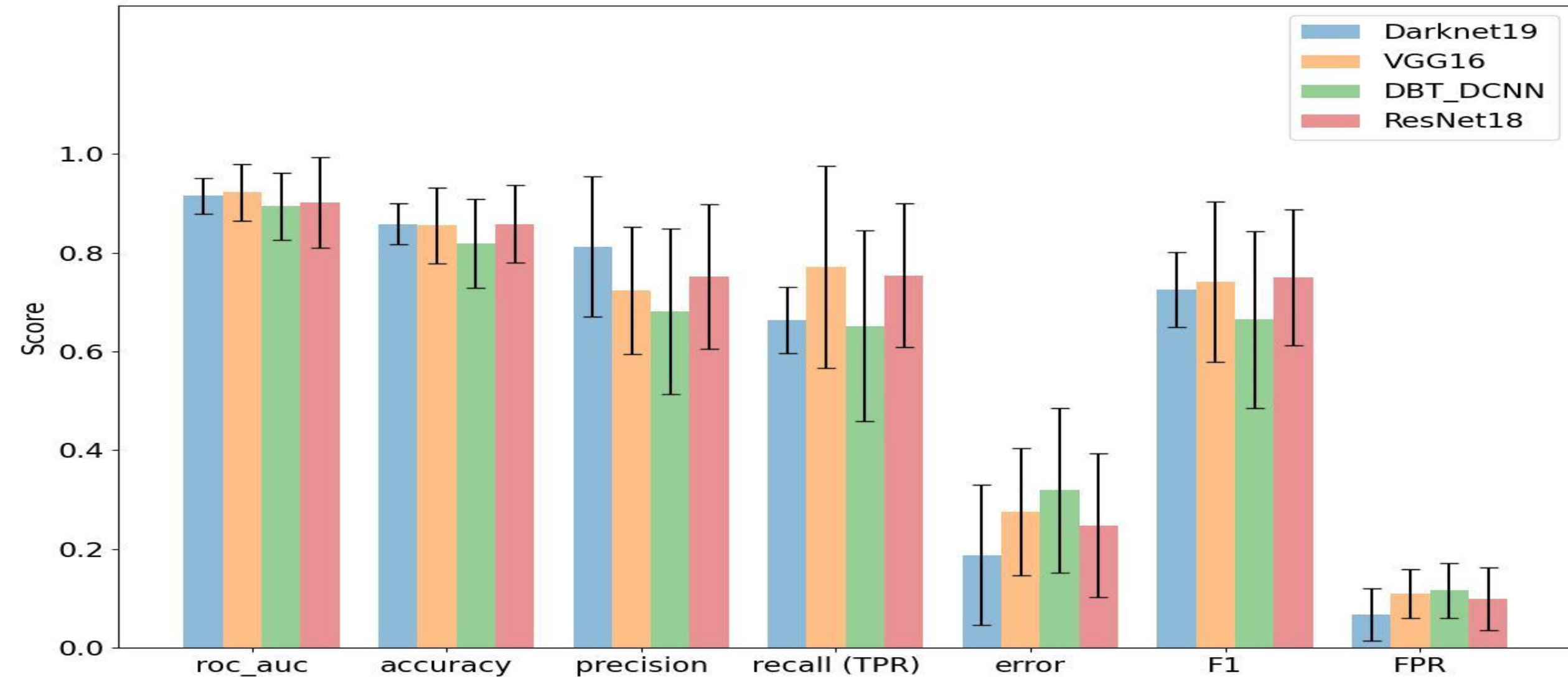


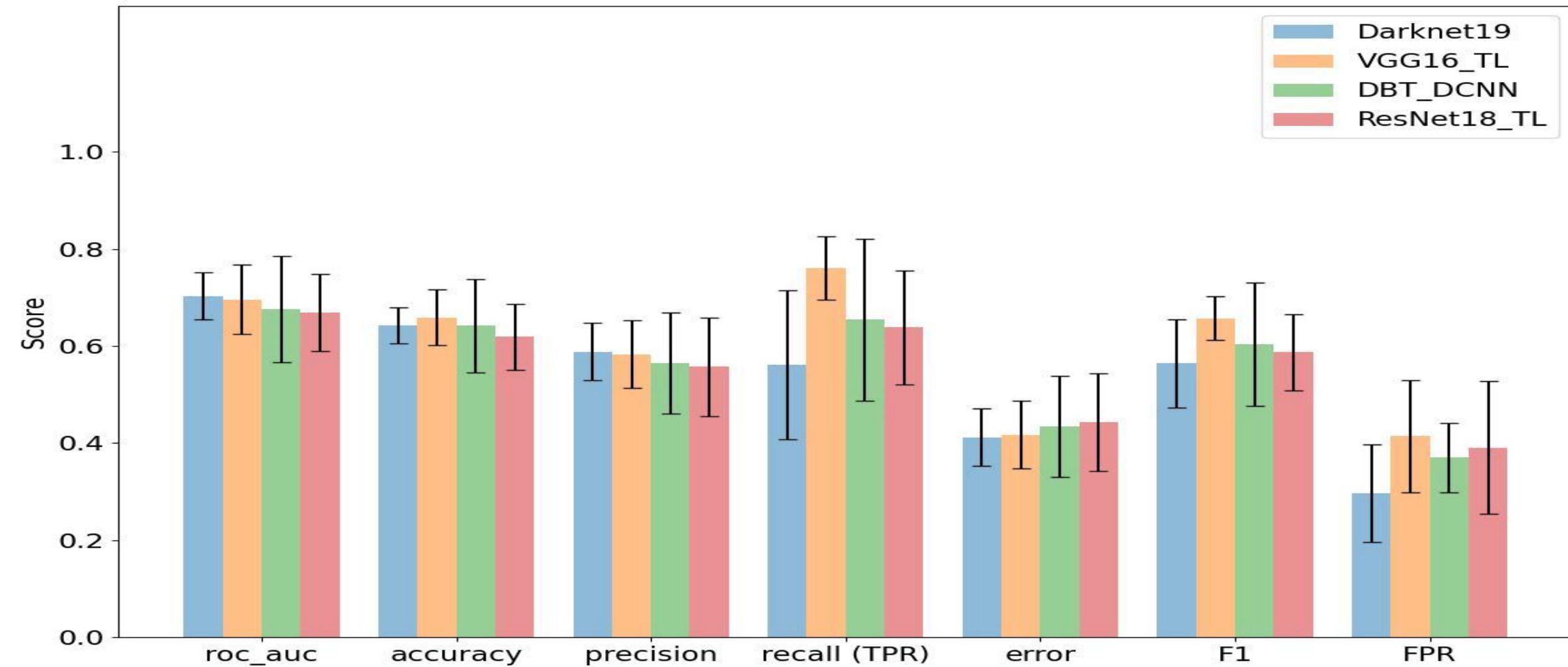
The DCNN-DBT was trained on a GPU NVIDIA GeForce RTX 3090 card (10496 CUDA cores, 24 GB GDDR6X video memory).

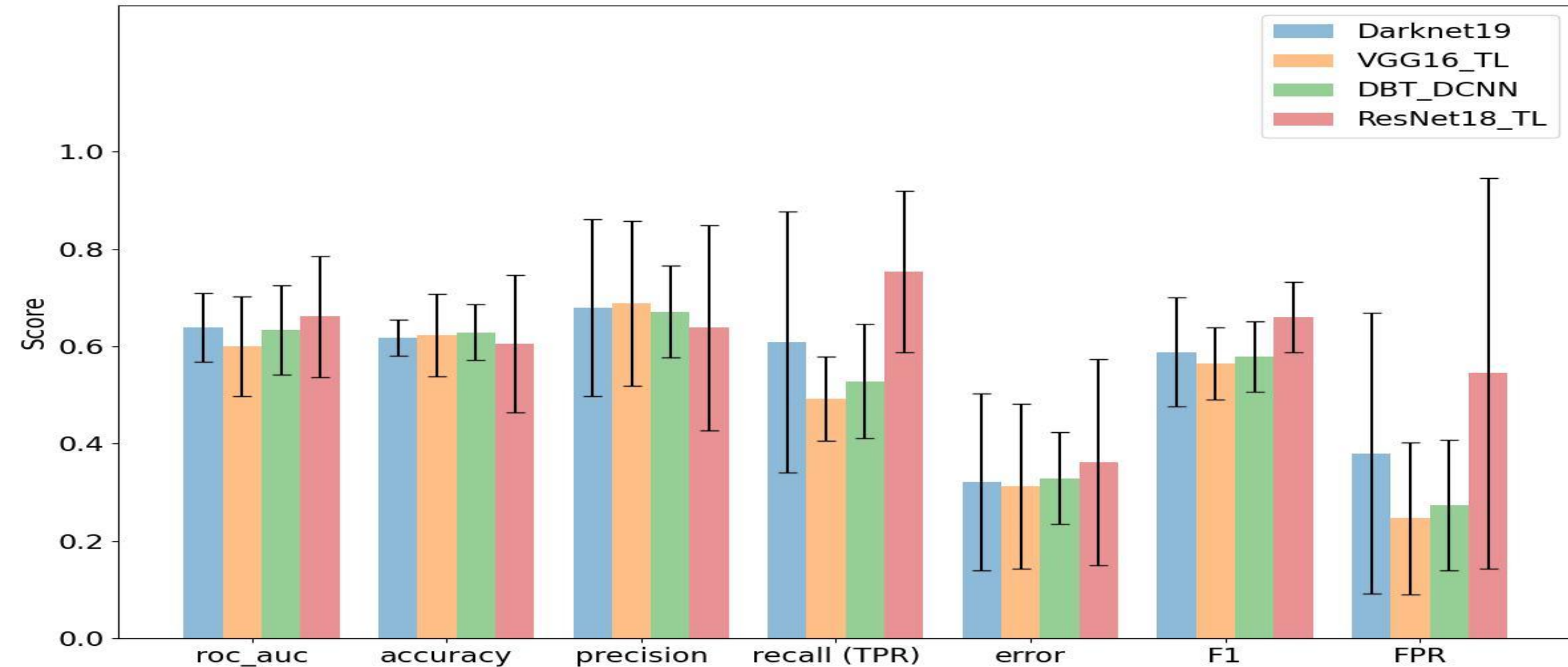
Patient 1 Dataset

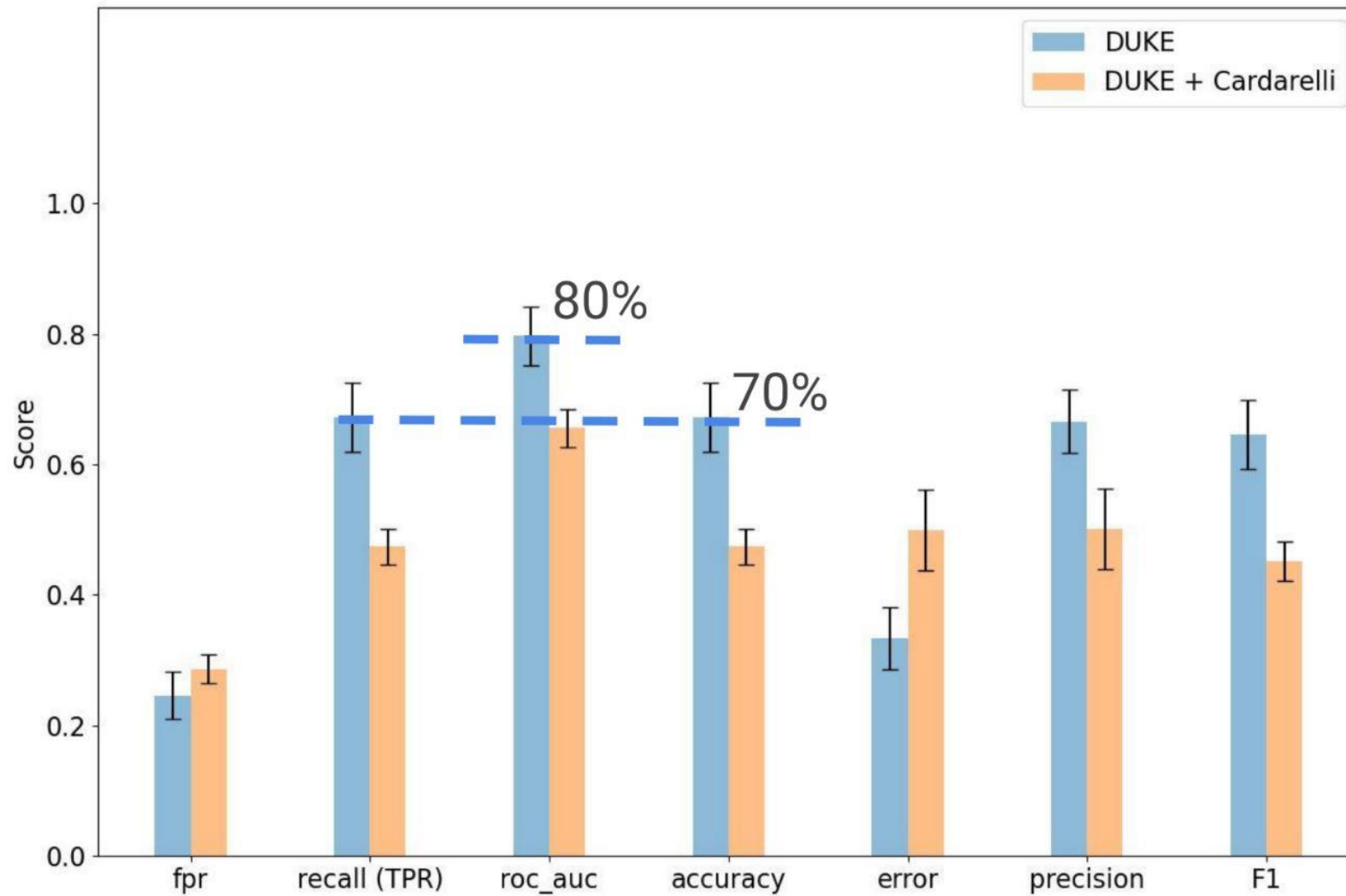










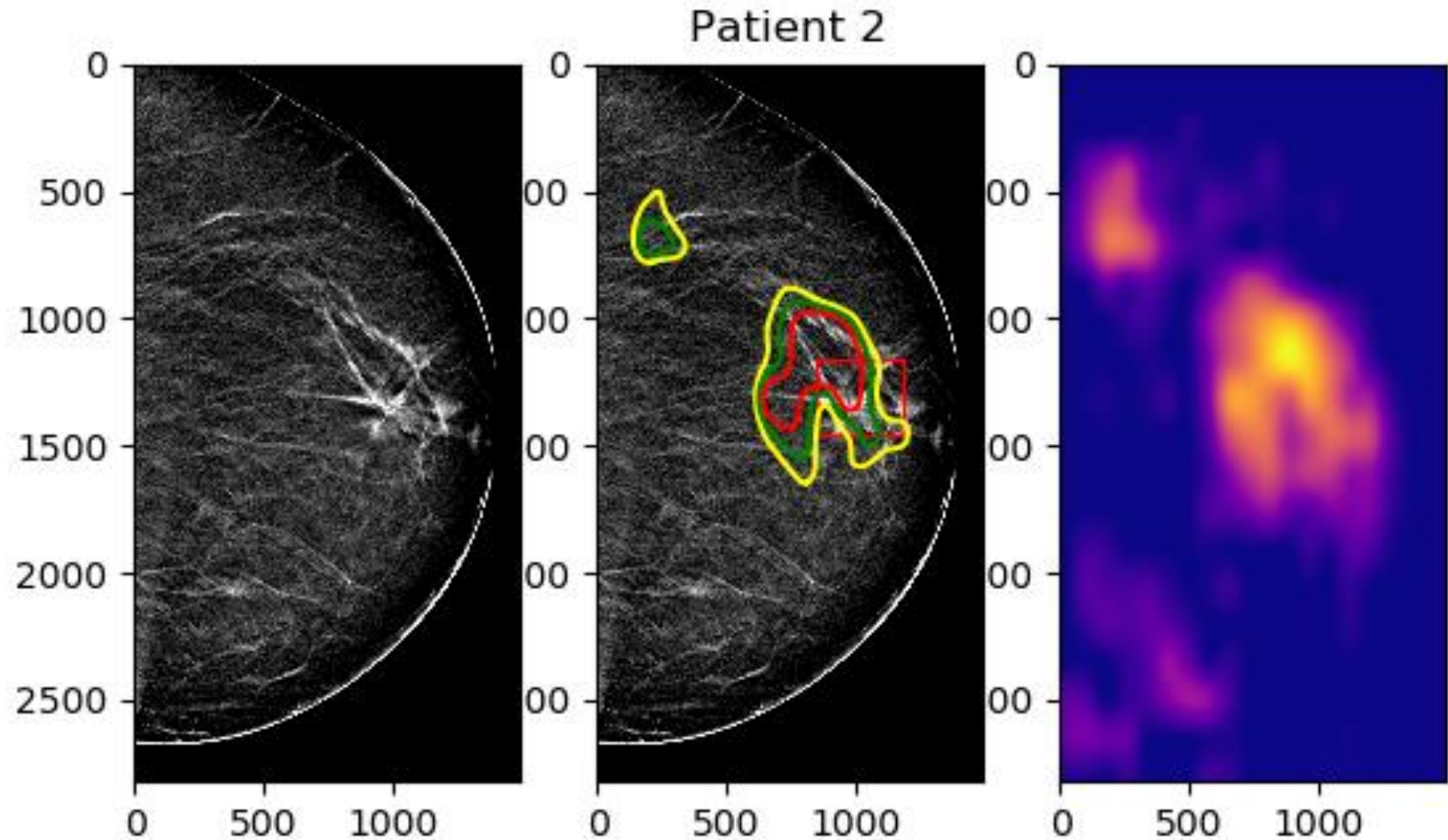


- Negative
- Benign masses
- Malignant masses



In this stage, for each identified slices is generated a Grad-CAM map to localize the maximum activation zone and consequently the possible localization of the mass with the definition of a Region of Interest (ROI).

- Yellow threshold level of 50%
- Green threshold level 60%
- Red threshold level 70%

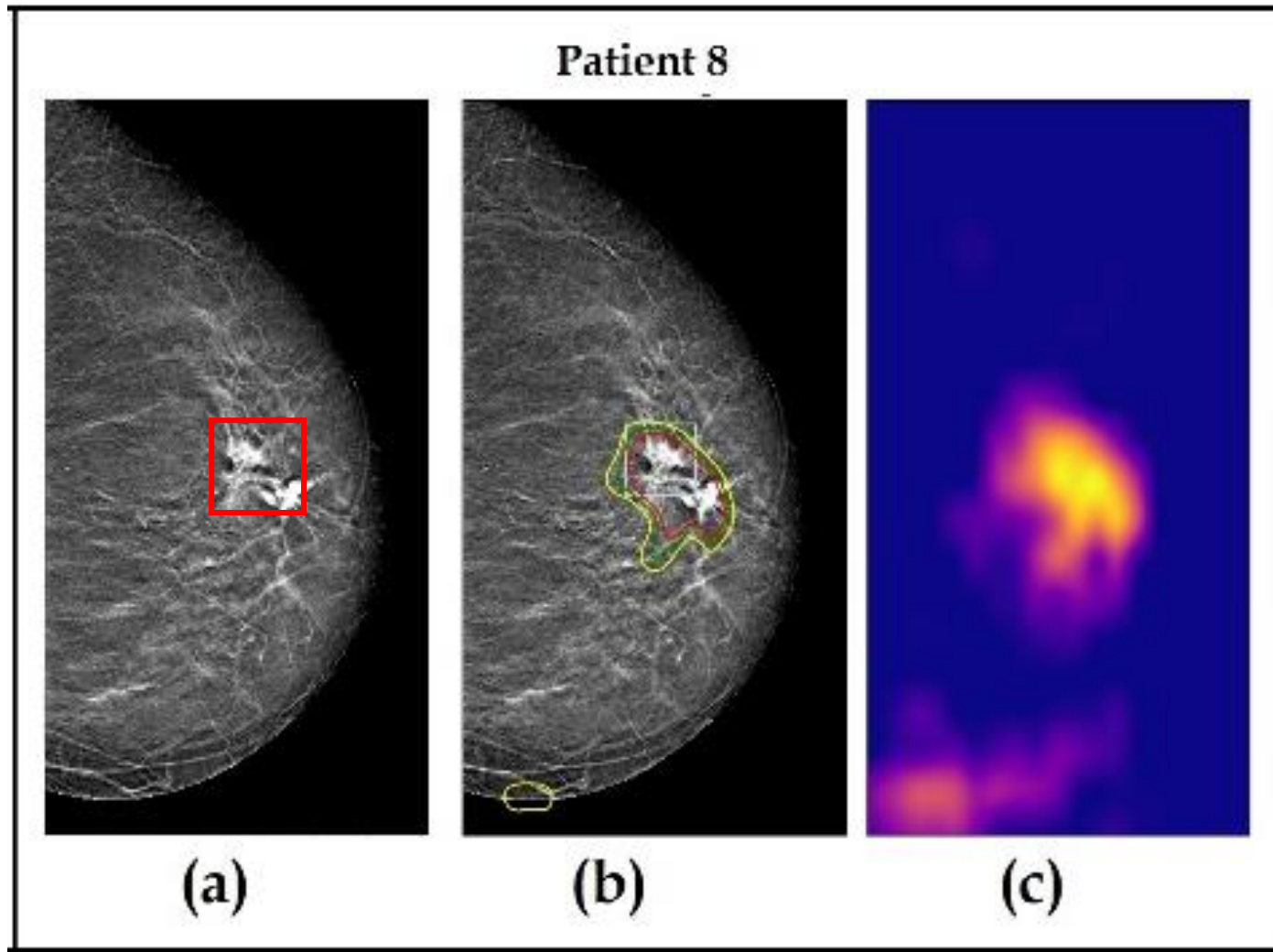


$$\textit{Overlap} = \frac{\textit{GradCAM ROI} \cap \textit{Ground Truth}}{\textit{Ground Truth}};$$

The ratio between the intersection of area of GradCAM ROI and the area indicated by the radiologist.

$$\textit{Activation} = \frac{\textit{GradCAM ROI dim}}{\textit{Image dim}}$$

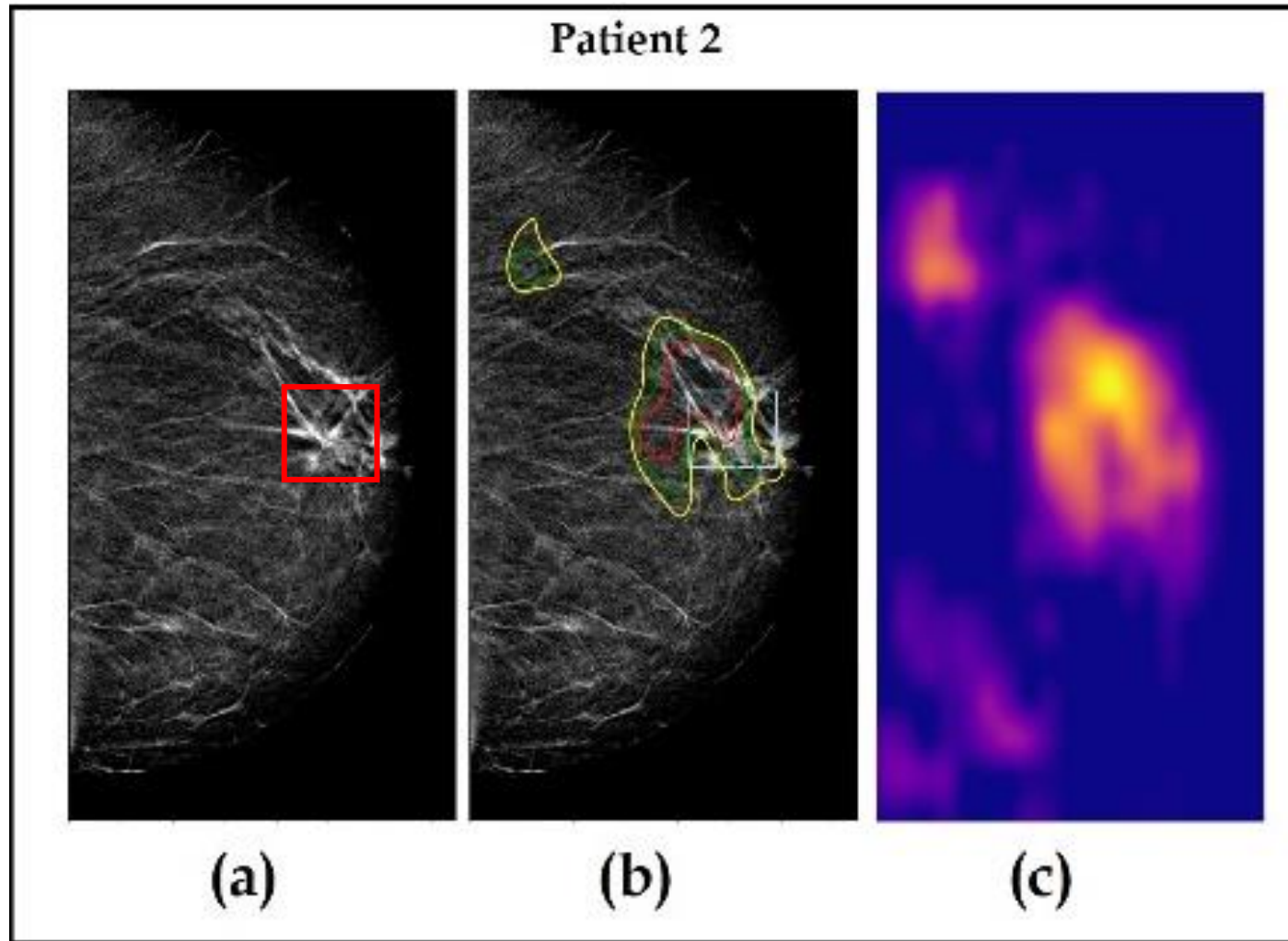
The ratio between the dimensions of GradCAM ROI and slice.



- Threshold > 0.5
 Overlap = 95%
 Activation = 15%

- Threshold > 0.6
 Overlap = 93%
 Activation = 10%

- Threshold > 0.7
 Overlap = 90%
 Activation = 8%

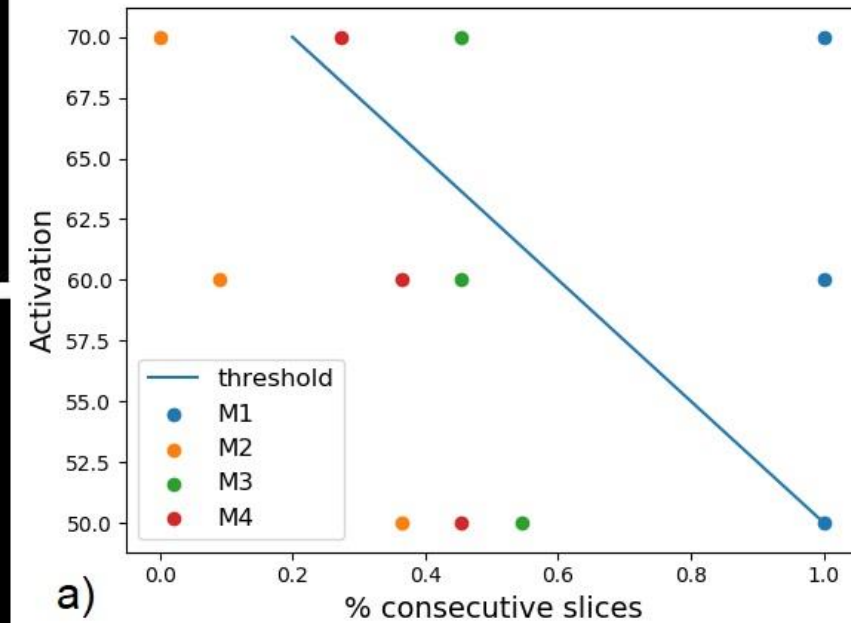
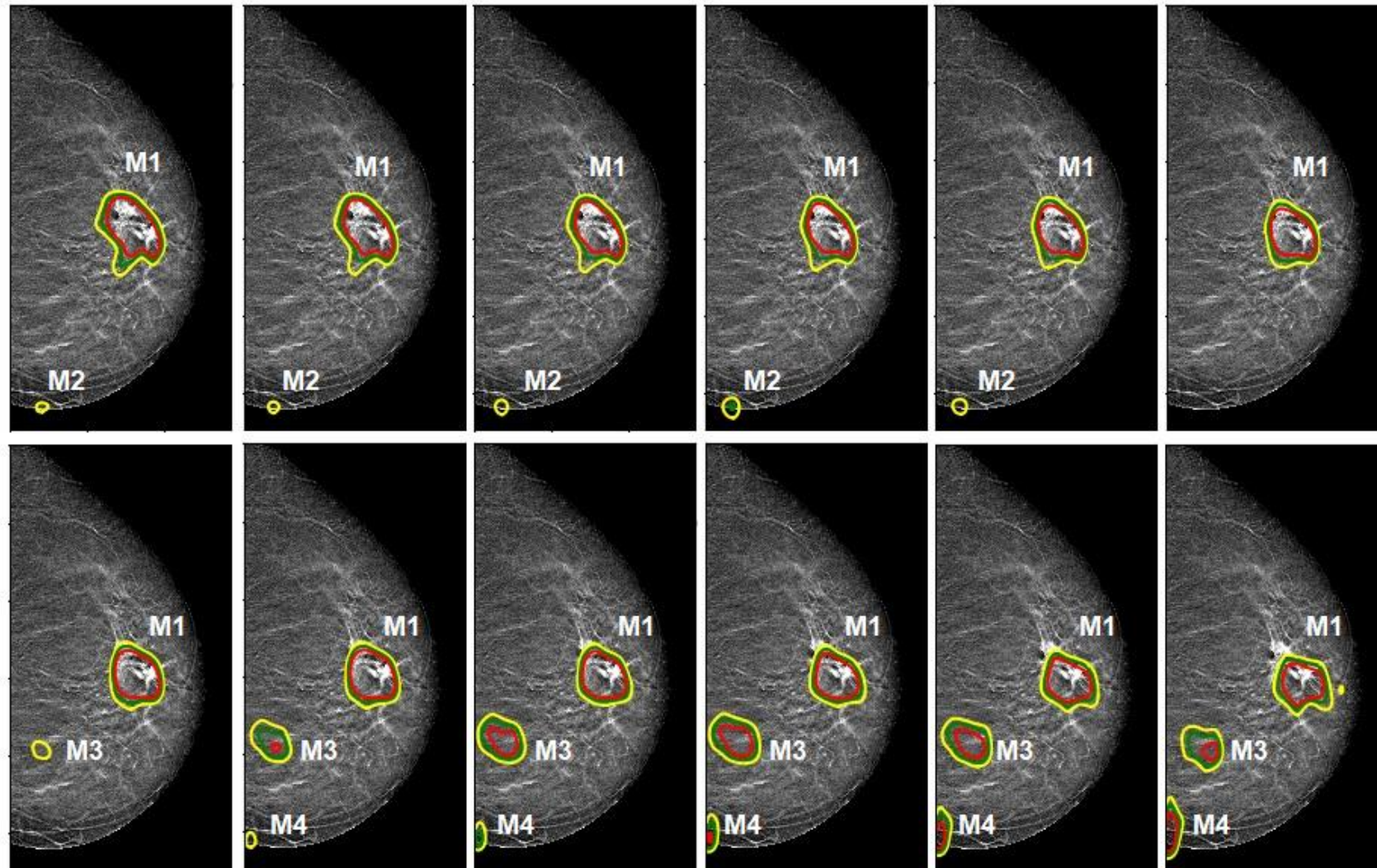


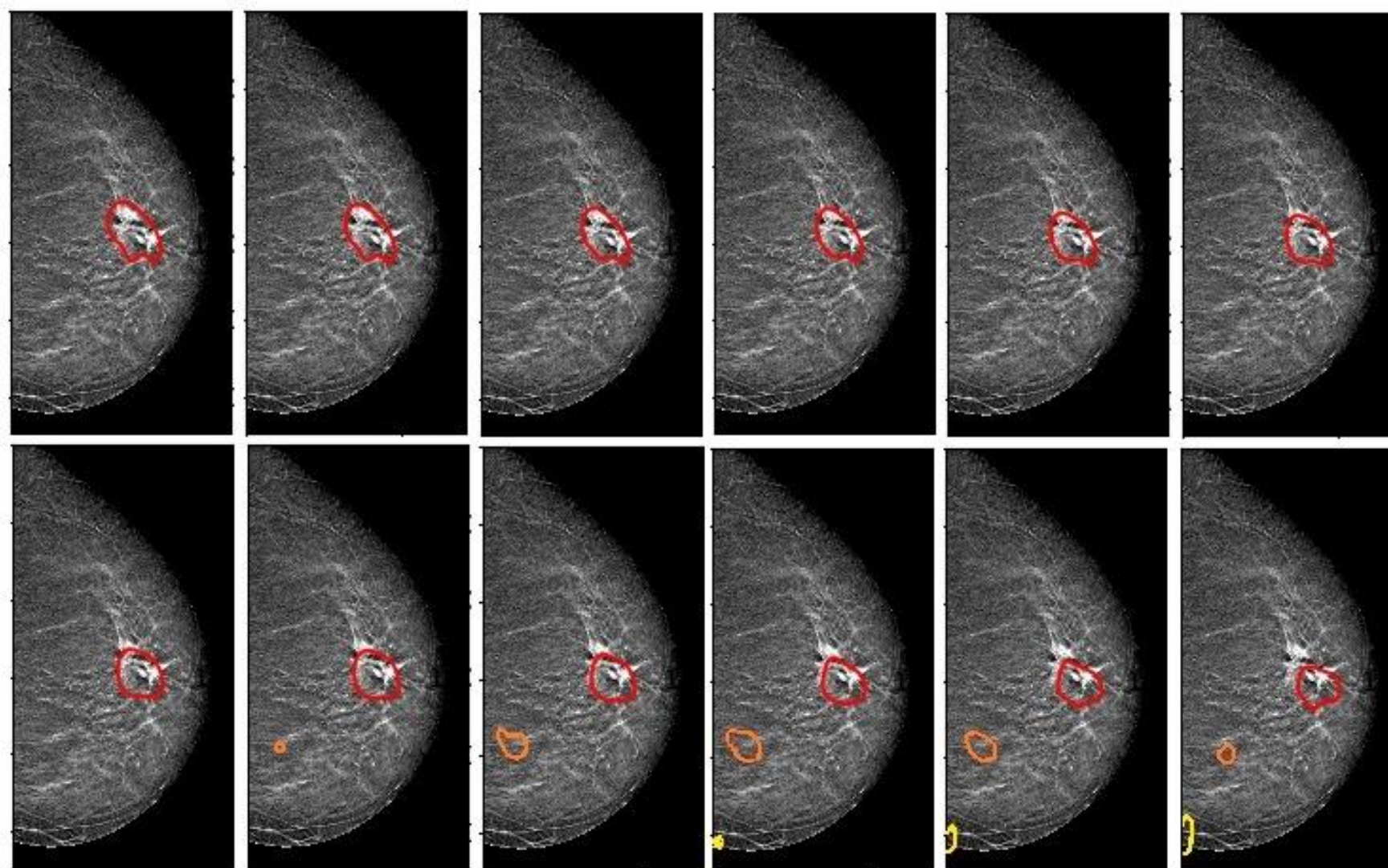
- Threshold > 0.5
 Overlap = 75%
 Activation = 25%

- Threshold > 0.6
 Overlap = 60%
 Activation = 15%

- Threshold > 0.7
 Overlap = 45%
 Activation = 10%

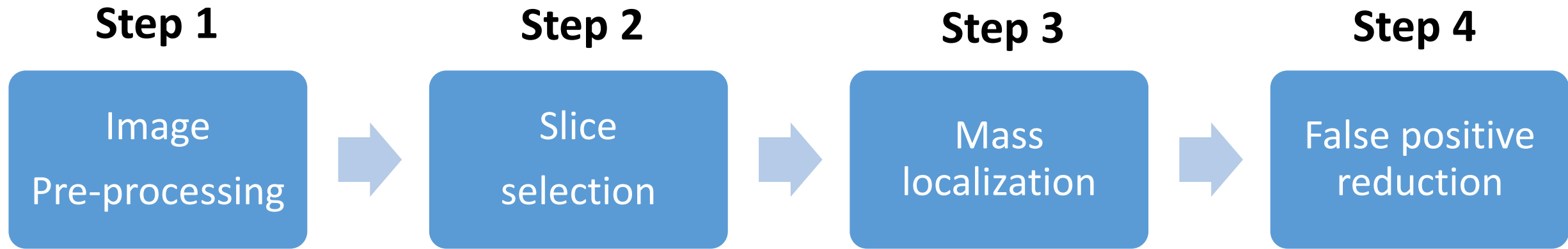
False positive reduction

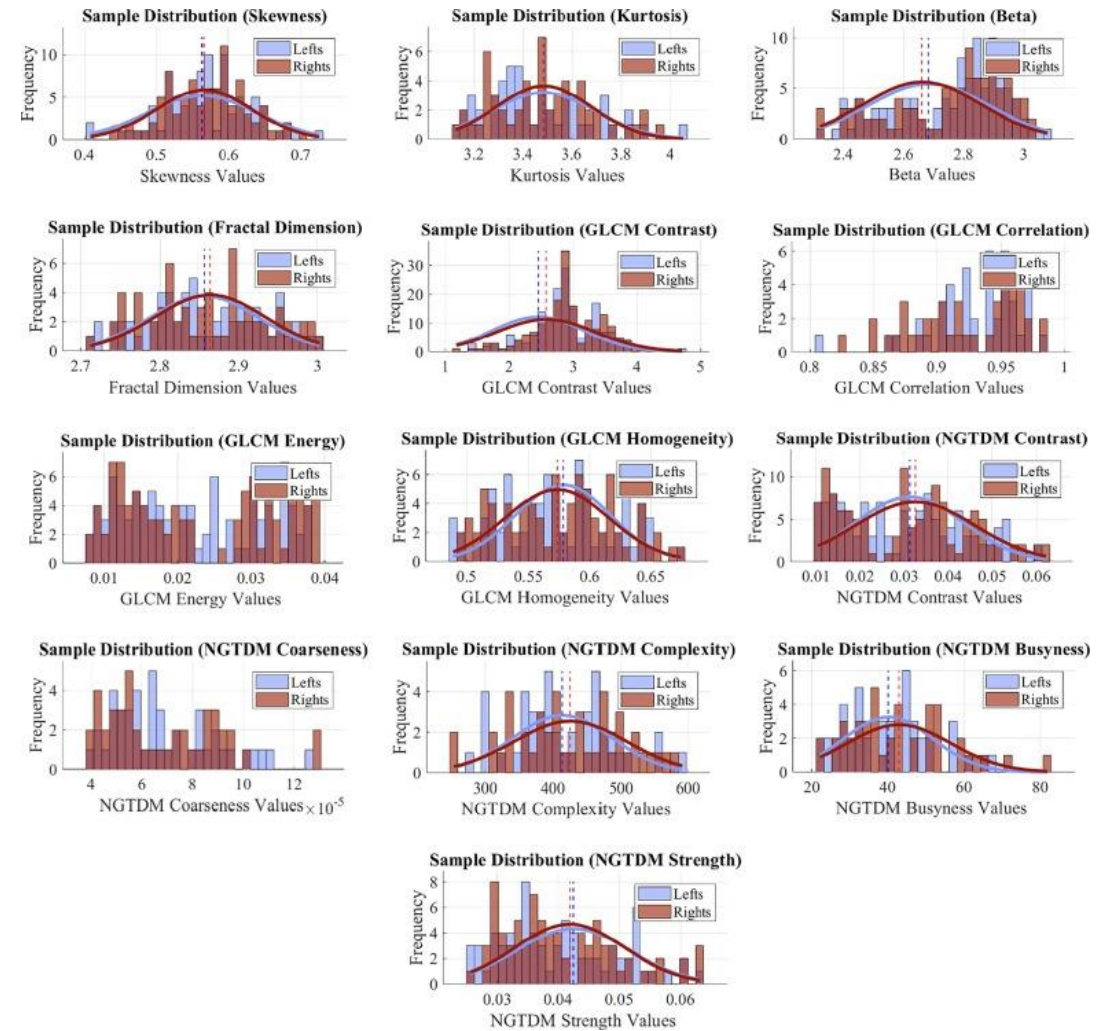
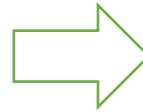
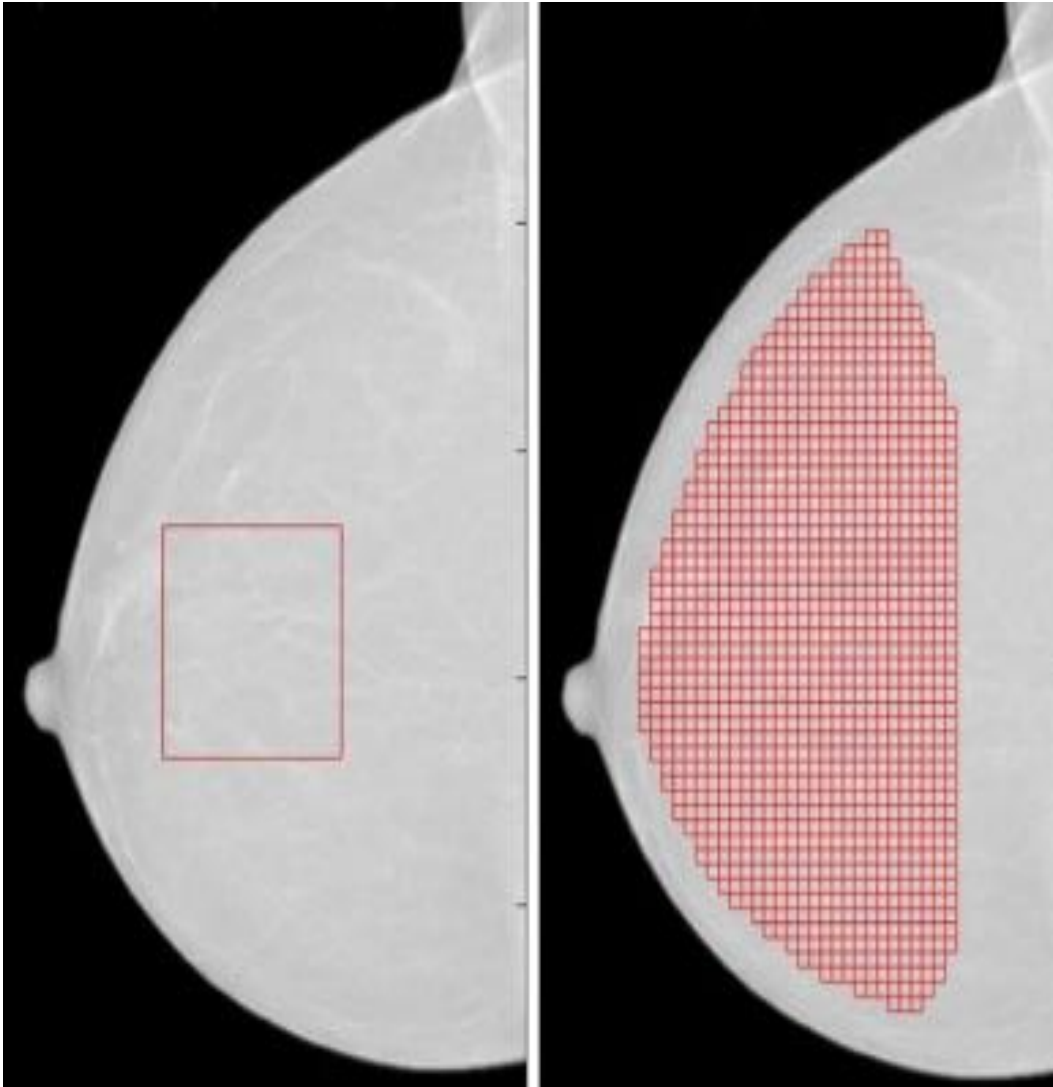




Confidence Level

- Low
- Medium
- High





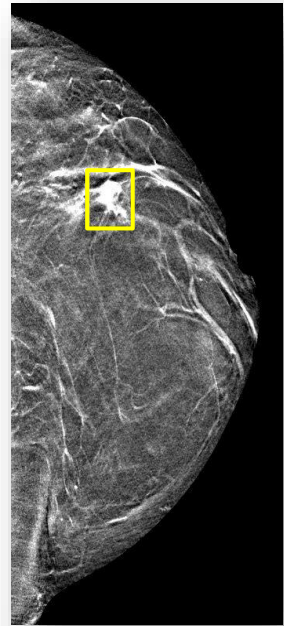
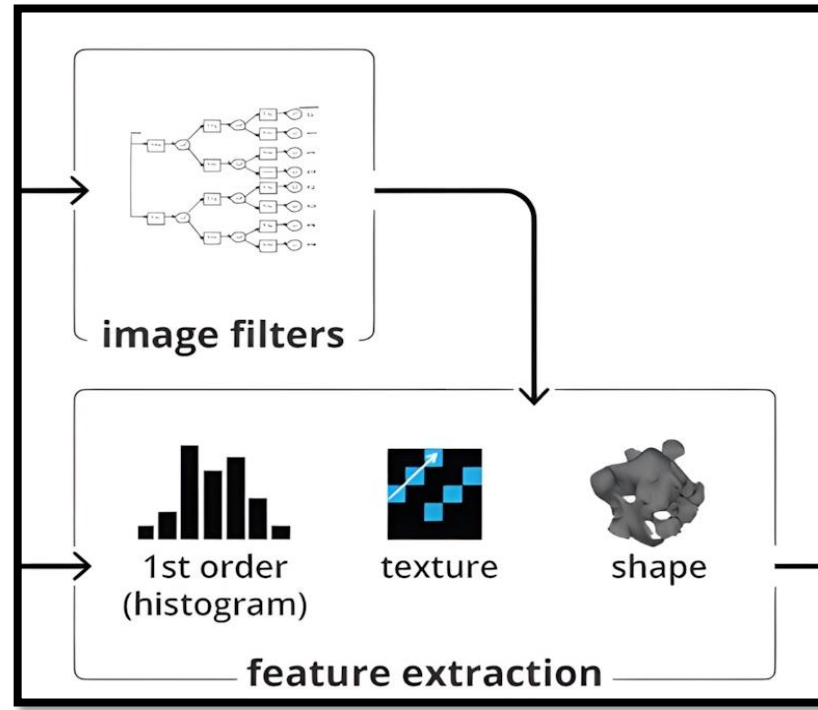
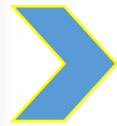
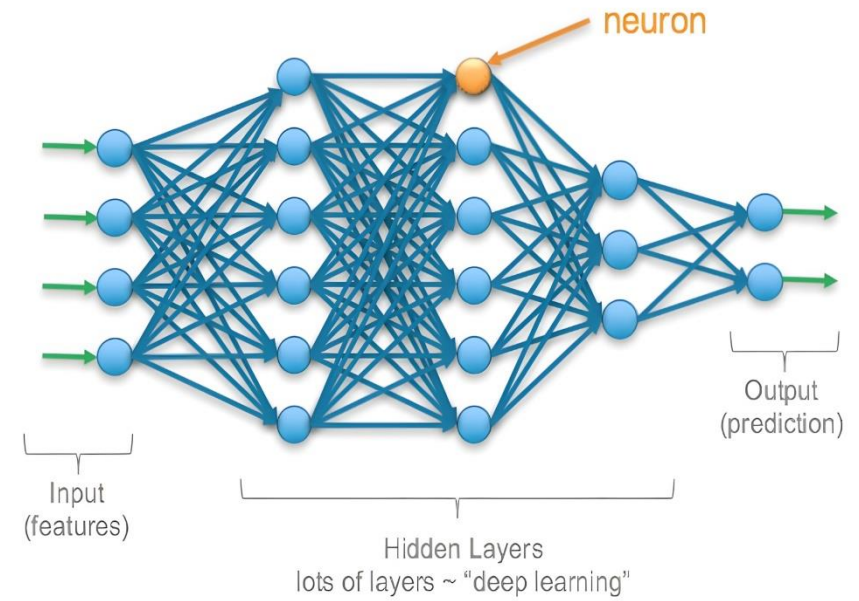
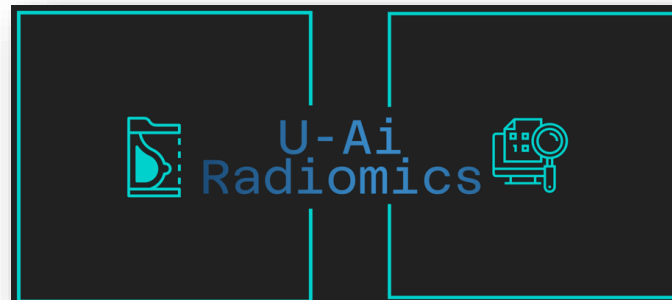


Image Segmentation



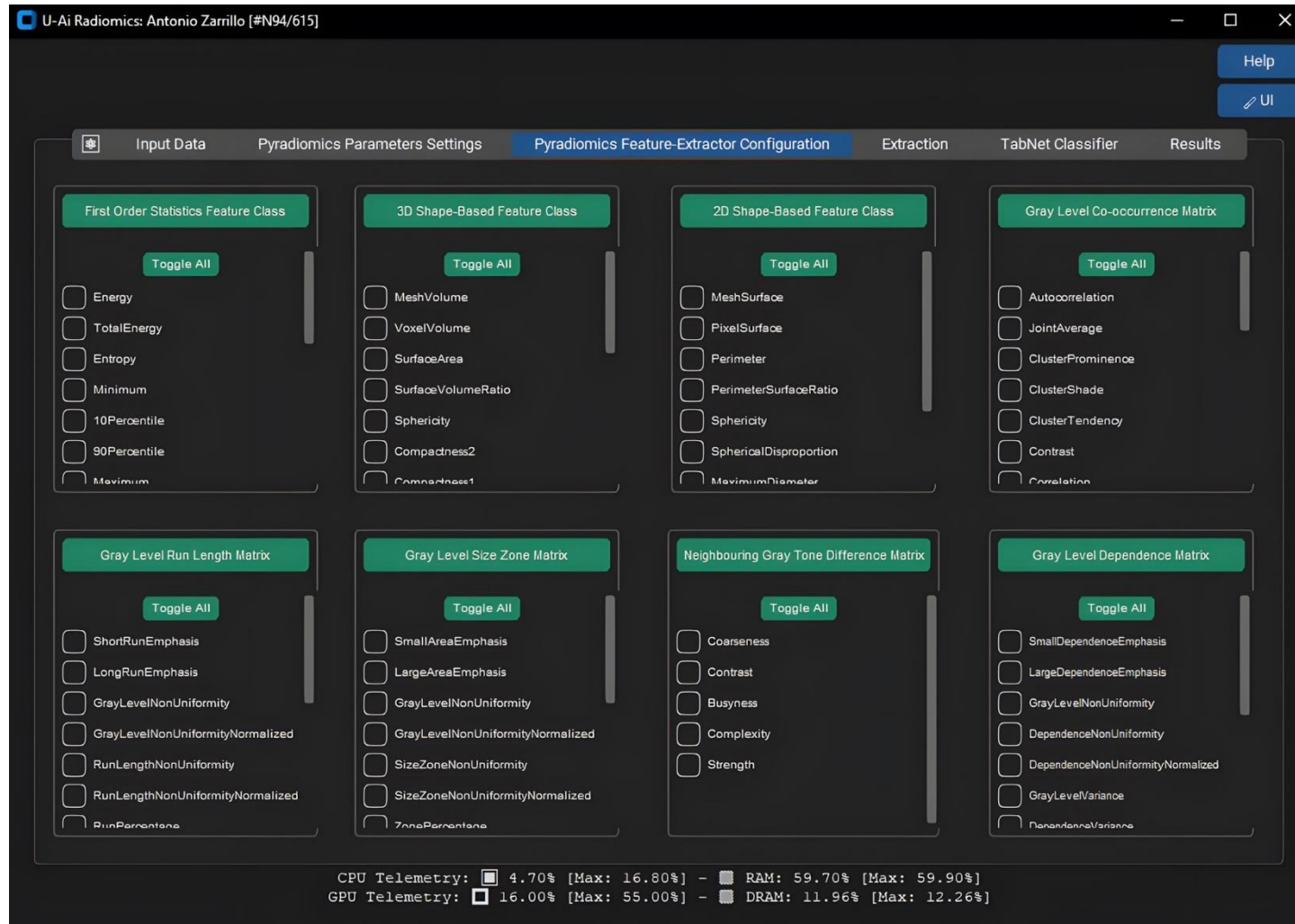
PyRadiomics



TabNet

La **PyRadiomics Parameters Settings Tab** consente di configurare i parametri di estrazione di PyRadiomics, distinguiamo tre livelli di settings:

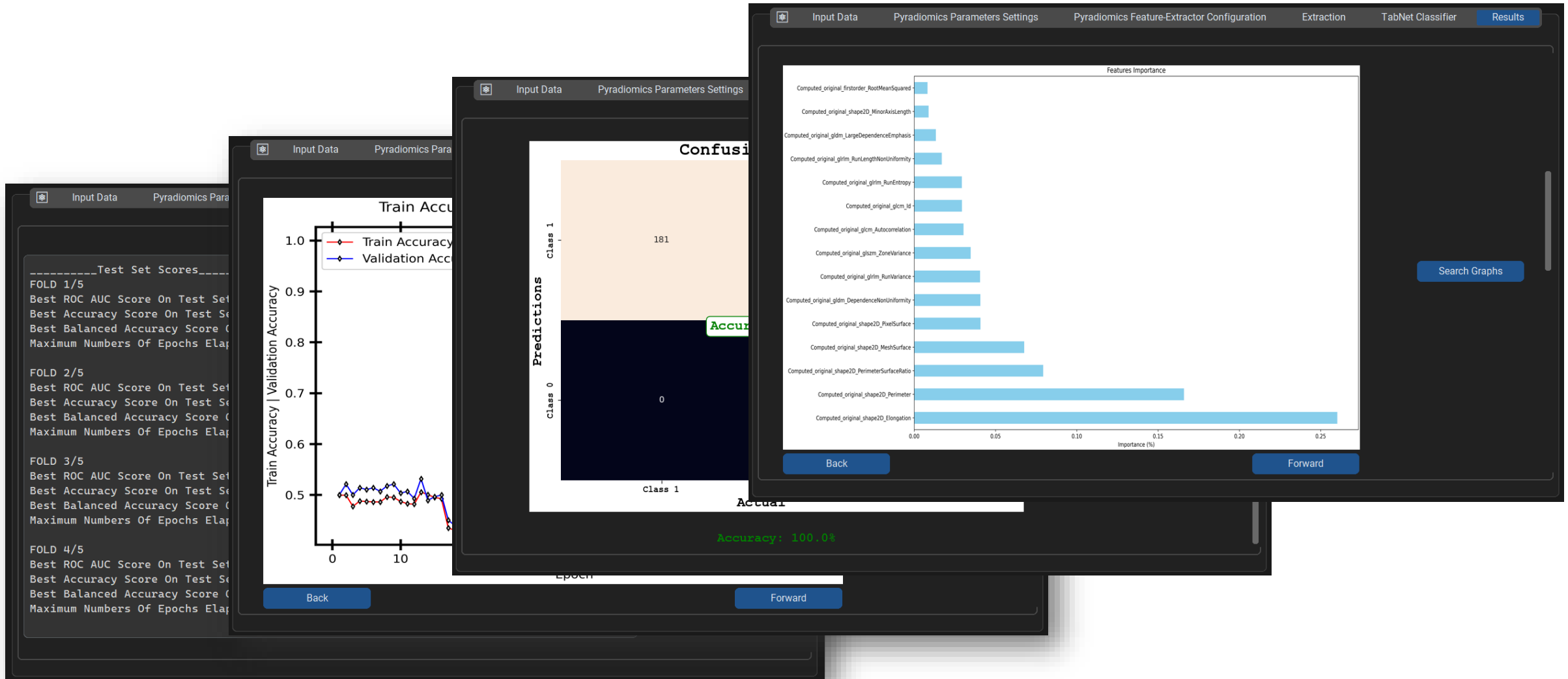
- **Feature Extractor Level (F.E.L.)**, per la pre-elaborazione delle immagini e della maschera (segmentazione);
- **Feature Class Level (F.C.L.)**, per la configurazione dei parametri del modulo *feature-extractor*;
- **Miscellaneous Info & Logger Verbosity**, per corredare l'estrazione di informazioni di contorno descrittive dei dati di input o del processo di estrazione.

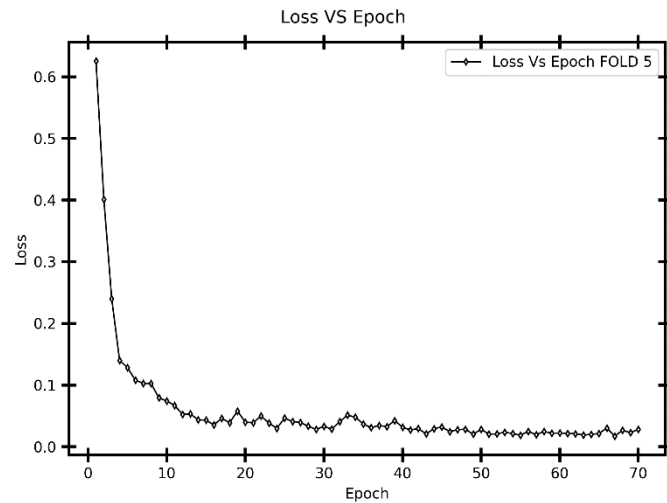
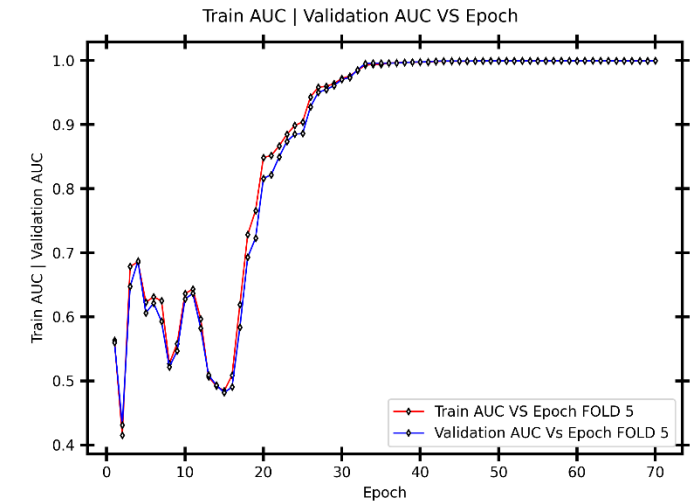
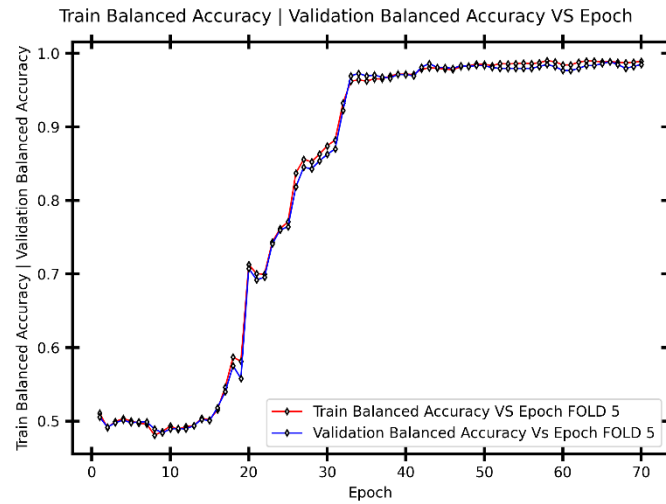
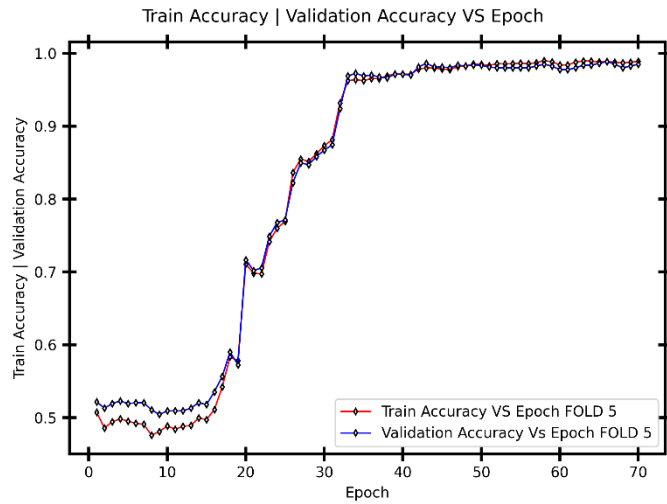


La **PyRadiomics Features Extractor Configuration Tab** consente di selezionare manualmente le features che il modulo feature-extractor andrà a calcolare entro la maschera di segmentazione:

- **First order statistics** - 1 classe, 19 features;
- **Shape features** - 2 classi, 27 features;
- **Texture features** - 5 classi, 74 features.

Totale: 8 classi, 120 features





CARD & I.F.O. (@ $N_d=31$)

Dataset Validazione			Dataset Test		
<i>Accuracy</i>	<i>Balanced Accuracy</i>	<i>AUC</i>	<i>Accuracy</i>	<i>Balanced Accuracy</i>	<i>AUC</i>
0.97 ± 0.01	0.97 ± 0.01	0.97 ± 0.01	0.946 ± 0.003	0.947 ± 0.004	0.947 ± 0.004

CARD&IFO (best model's Folds' Top 5%)

CARD	Features	Max Folds'	Importance (%)
	Computed_original_shape2D_MajorAxisLength		22.57
	Computed_original_shape2D_Elongation		22.14
	Computed_original_shape2D_MeshSurface		17.24
	Computed_original_shape2D_MinorAxisLength		14.40
	Computed_original_gldm_DependenceNonUniformity		13.15
	Computed_original_shape2D_PerimeterSurfaceRatio		11.55
	Computed_original_shape2D_Perimeter		8.50
	Computed_original_gldm_DependenceEntropy		8.47
	Computed_original_shape2D_PixelSurface		8.40
	Computed_original_gldm_ClusterShade		6.06
	Computed_original_glszm_SizeZoneNonUniformity		5.92
	Computed_original_shape2D_MaximumDiameter		5.65

IFO	Features	Max Folds'	Importance (%)
	Computed_original_shape2D_MaximumDiameter		19.69
	Computed_original_shape2D_Elongation		18.65
	Computed_original_shape2D_MinorAxisLength		15.25
	Computed_original_glrlnm_RunLengthNonUniformity		14.84
	Computed_original_gldm_HighGrayLevelEmphasis		10.80
	Computed_original_shape2D_Perimeter		8.02
	Computed_original_shape2D_PerimeterSurfaceRatio		7.67
	Computed_original_firstorder_TotalEnergy		6.33
	Computed_original_firstorder_10Percentile		5.29
	Computed_original_shape2D_MeshSurface		5.03
	Computed_original_shape2D_MajorAxisLength		3.69
	Computed_original_firstorder_Range		3.63

CARD&IFO N_d = 48 Vs SK=OFF (best model's Folds' Top 5%)

	Features	Max Folds'	Importance (%)
	Computed_original_shape2D_MinorAxisLength		17.12
	Computed_original_shape2D_Elongation		16.63
	Computed_original_shape2D_MajorAxisLength		12.13
	Computed_original_shape2D_MaximumDiameter		10.52
	Computed_original_gldm_DependenceNonUniformity		9.45
	Computed_original_glszm_SizeZoneNonUniformity		9.23
	Computed_original_shape2D_Perimeter		8.47
	Computed_original_shape2D_PerimeterSurfaceRatio		7.23
	Computed_original_shape2D_MeshSurface		7.11
	Computed_original_glrlnm_RunLengthNonUniformity		6.87
	Computed_original_firstorder_Energy		5.28
	Computed_original_shape2D_PixelSurface		4.92
	Computed_original_gldm_Correlation		4.61
	Computed_original_gldm_ClusterShade		4.23
	Computed_original_gldm_MCC		3.63
	Computed_original_firstorder_Skewness		3.60
	Computed_original_gldm_Autocorrelation		3.51
	Computed_original_ngtdm_Strength		3.46
	Computed_original_firstorder_Range		3.28
	Computed_original_firstorder_TotalEnergy		3.20
	Computed_original_gldm_DependenceNonUniformityNormalized		3.20
	Computed_original_firstorder_Variance		3.04
	Computed_original_ngtdm_Complexity		2.87
	Computed_original_glszm_SmallAreaLowGrayLevelEmphasis		2.87

CARD & IFO

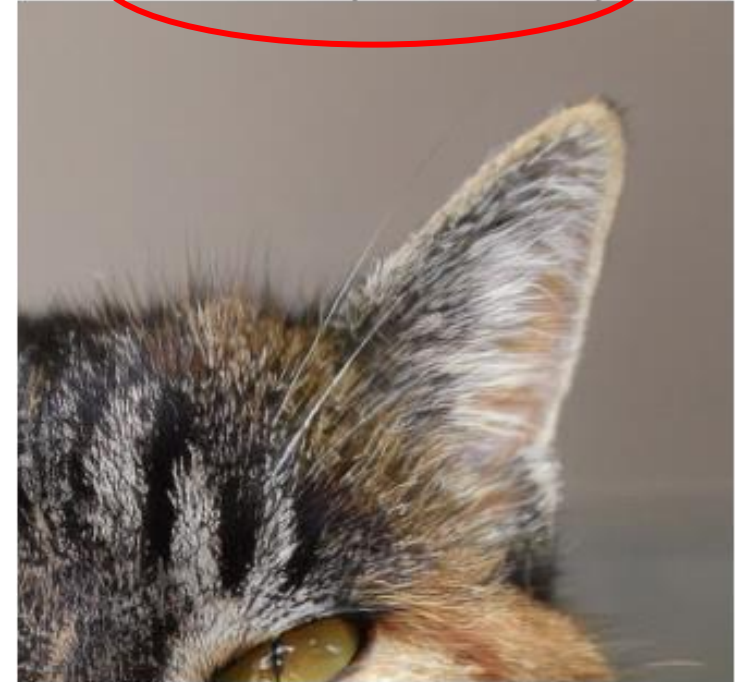
Original (118x124)



EDSR (472x496)



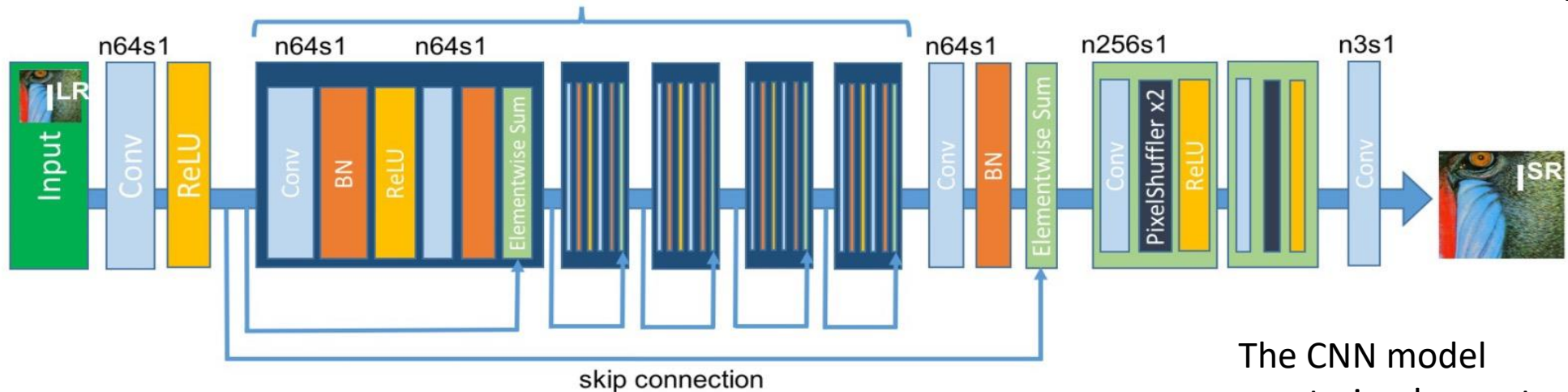
SRGAN (472x496)



GAN model architecture

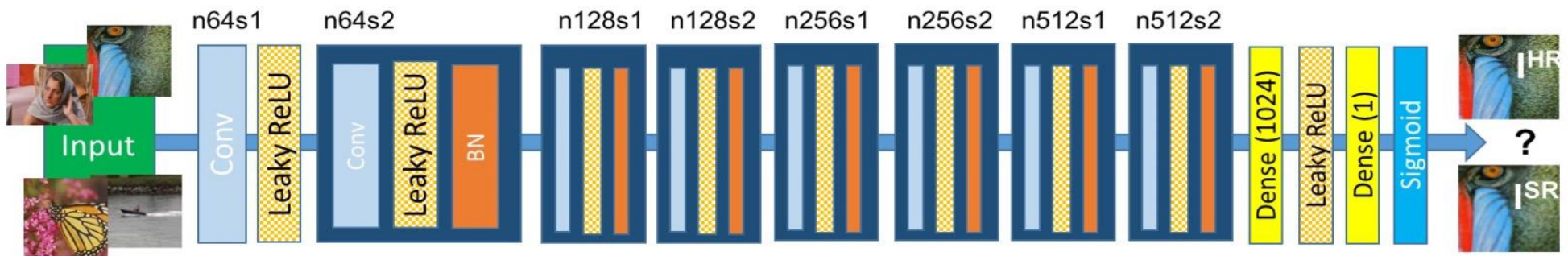
- SRGAN model → 1.55M parameters
- Common input shape → (512×512)

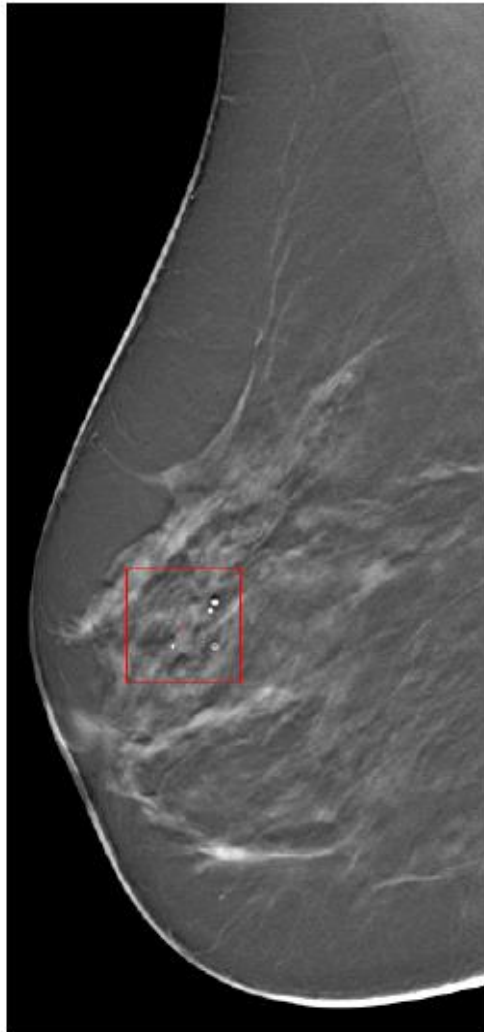
Generator Network



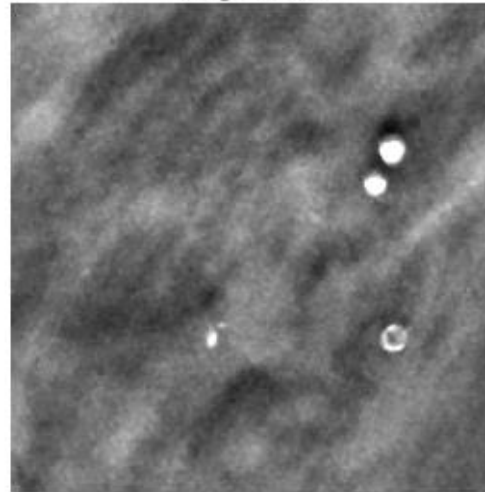
The CNN model was trained on natural images (DIV2K dataset)

Discriminator Network

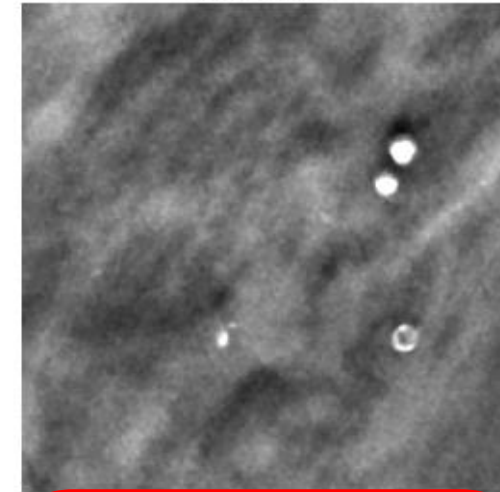




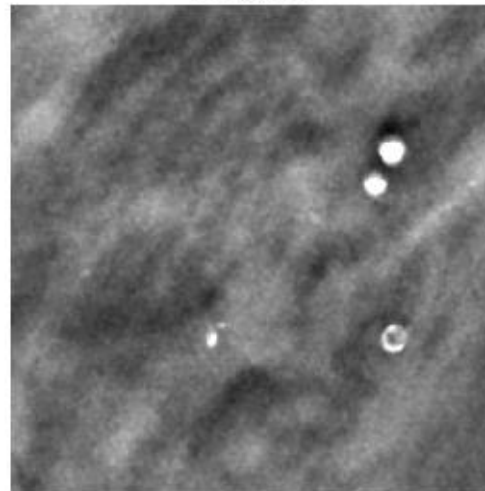
Original ROI



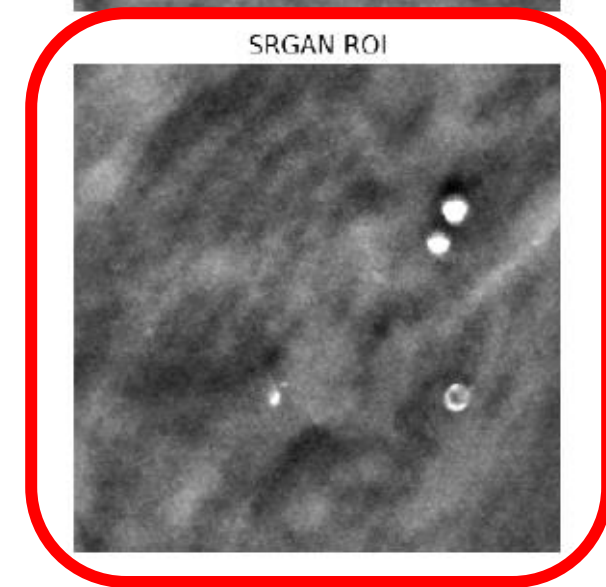
Bicubic ROI



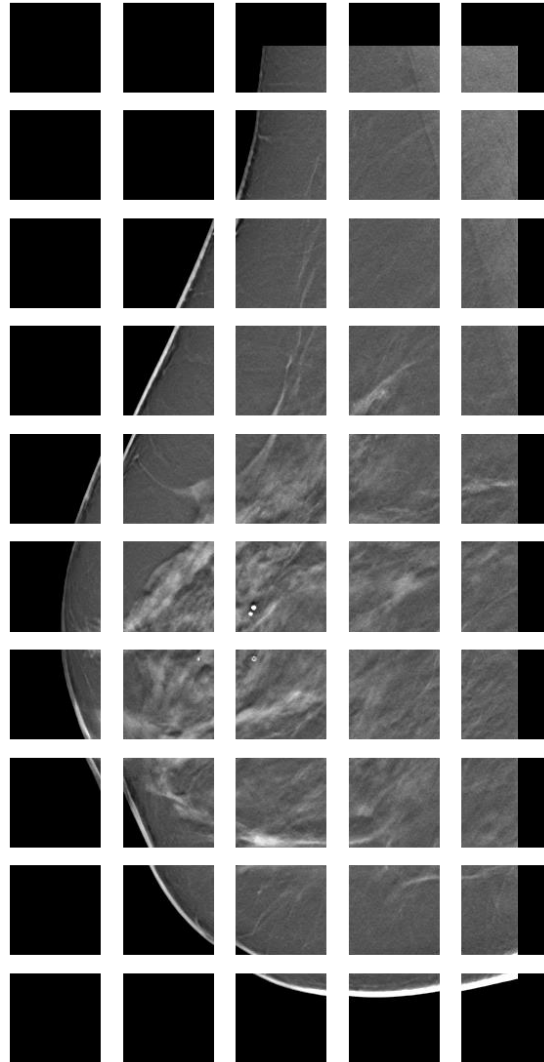
EDSR ROI



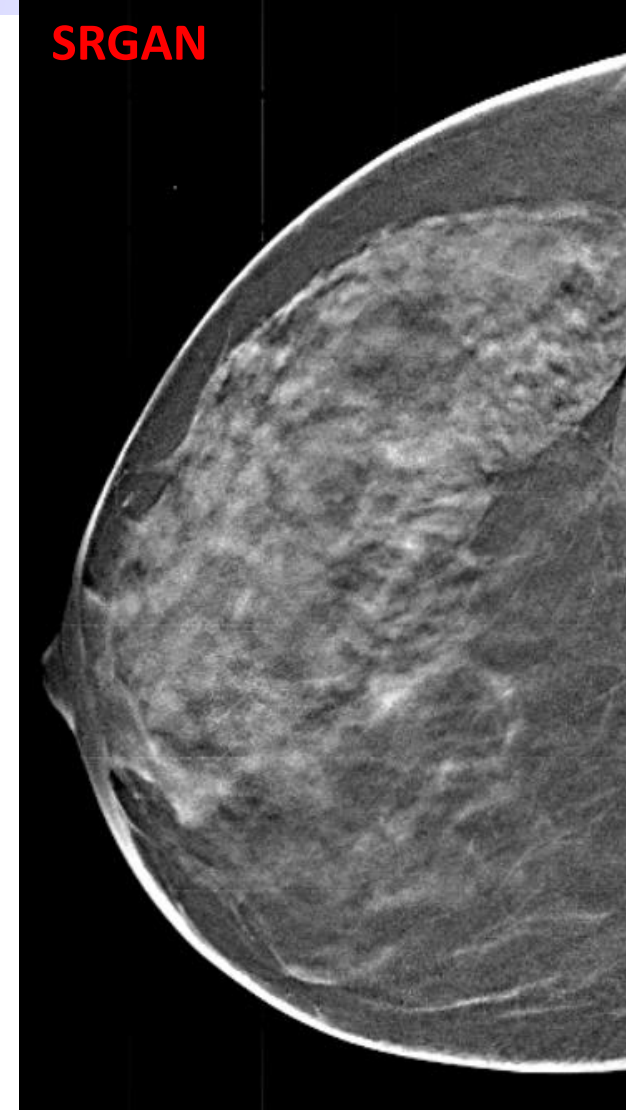
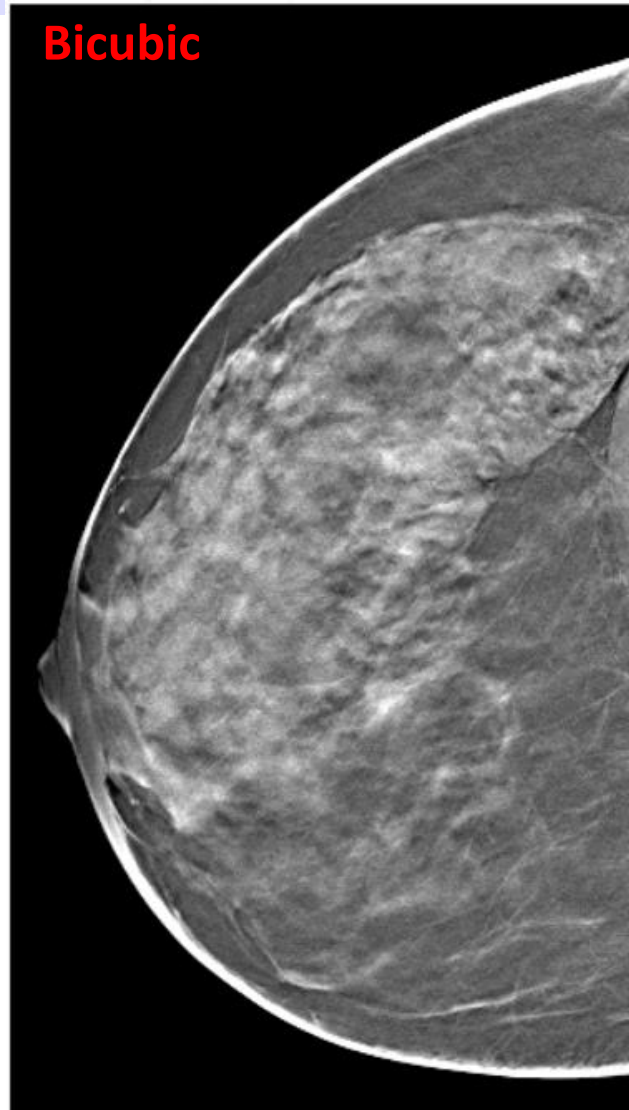
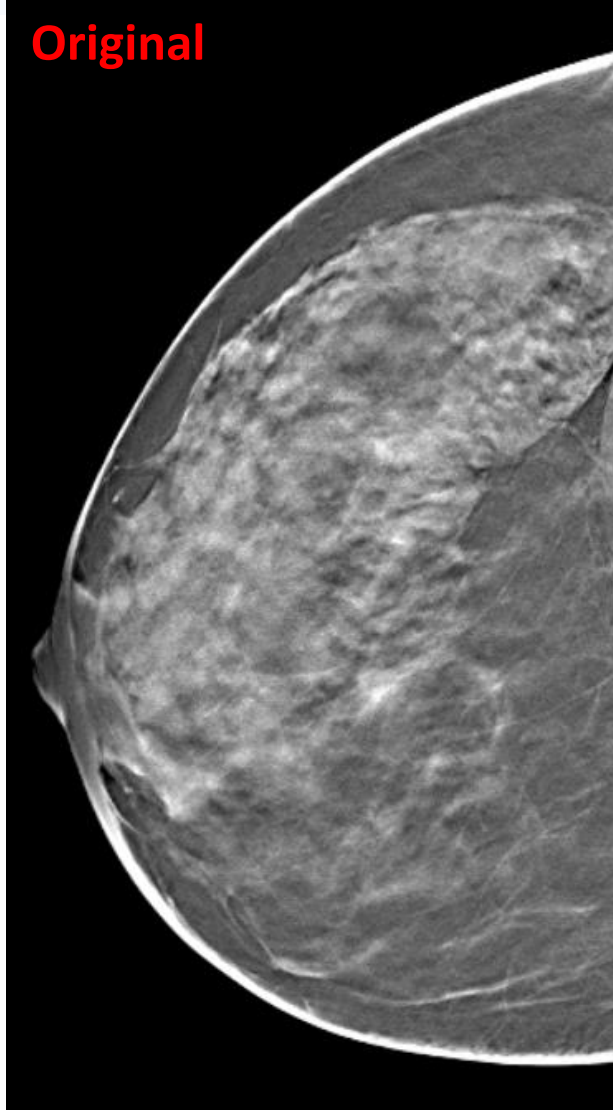
SRGAN ROI

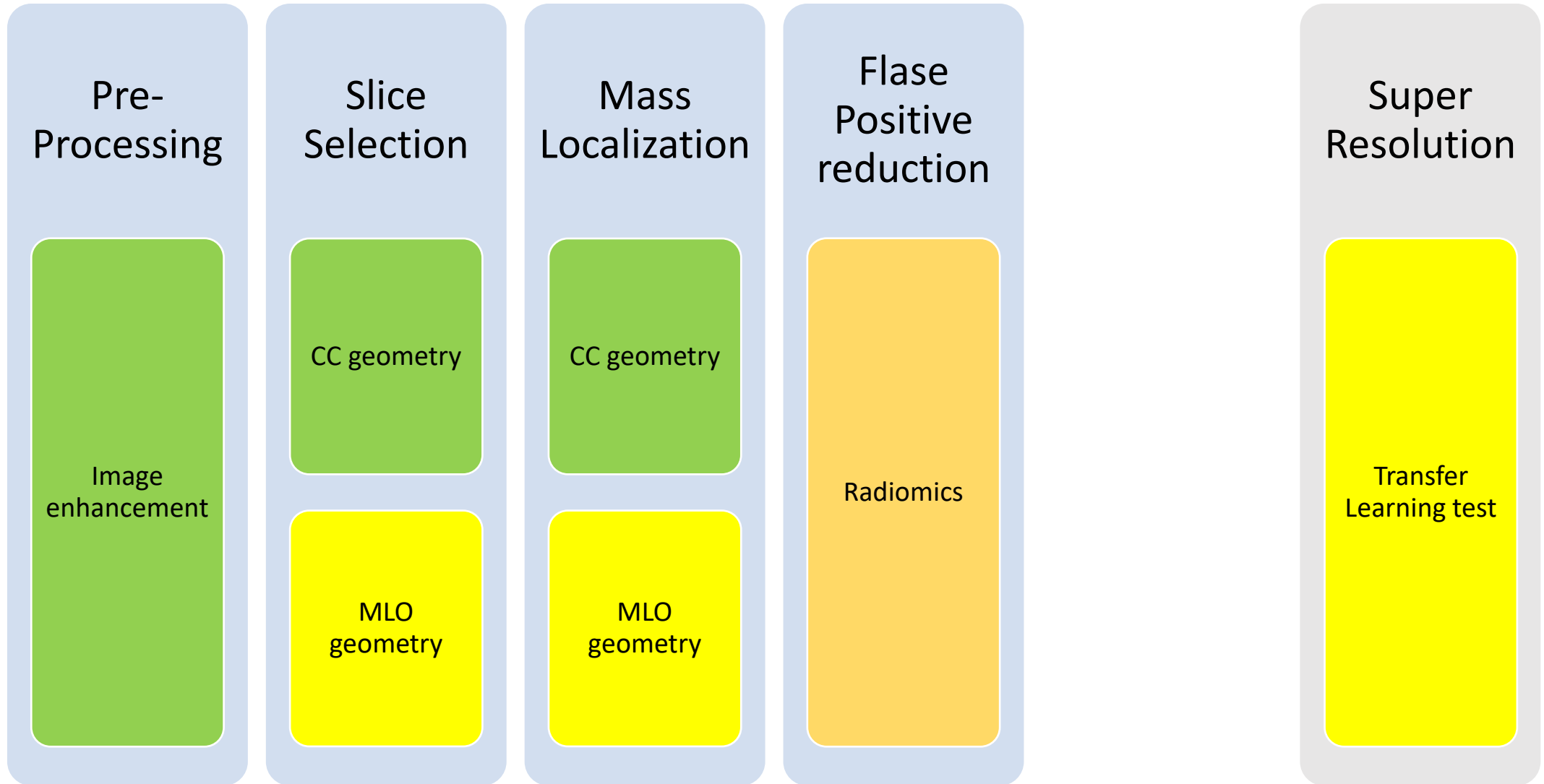


- Current input shape
2400x1100 ← **unfeasible**
- Split image into a series of
disjointed patches
(256x256)
- Monitor the boundary effect
related to image
reconstruction



Computational time
requires for the SR of the
entire image is
around 7s





Grazie per l'attenzione



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