



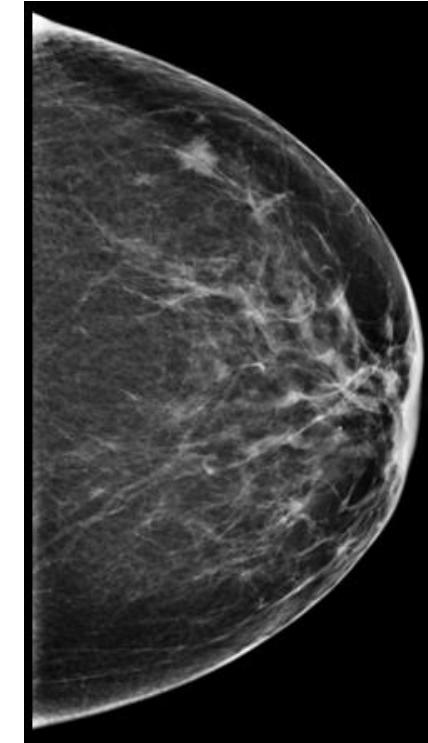
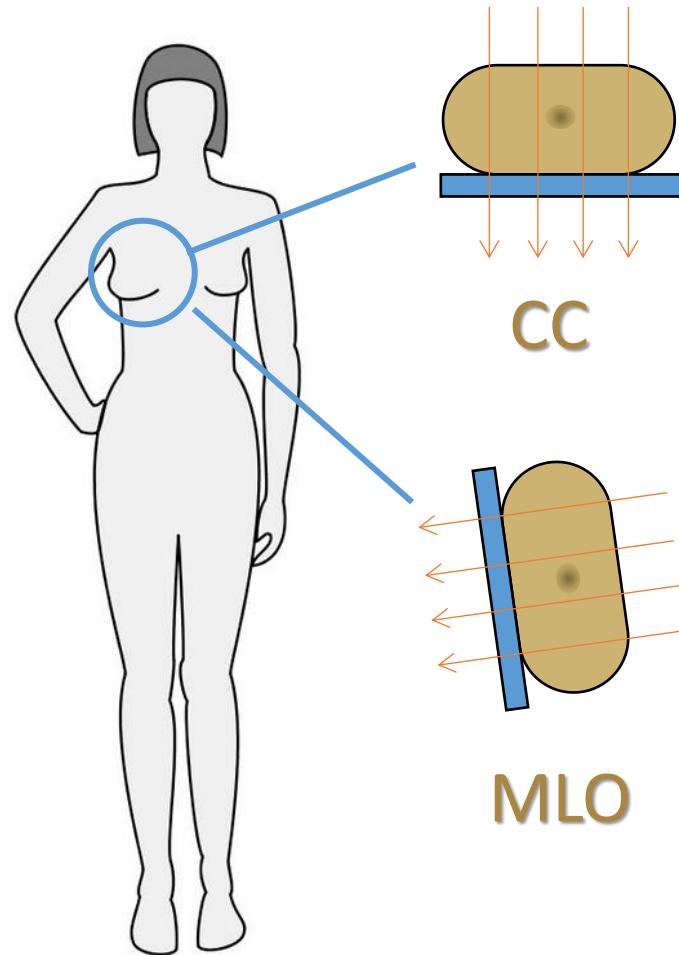
AI for Digital breast Tomosynthesis



```
1100 1101 0000 1100 0001 1000 0111 1000 0100 1100 0001 0010 1100 0100 0001 1110 0000 1000 1011 1100 1111
0000 1110 0011 1000 0110 0000 1110 0110 0111 0000 0100 0011 1100 0001 1110 1000 0011 1110 0001 1100 1000
0001 0111 1000 1001 1011 0110 1110 0011 1111 1100 1100 0101 1100 1100 0110 0000 0000 0100 1001 1001
1110 1001 1100 0000 1111 0110 1100 0011 0101 0000 1100 1101 1111 1100 0000 1111 1000 1100 0010 1111
1111 0110 1000 1001 0110 0000 0011 0100 0000 1101 0111 1111 0100 1100 1111 1110 0110 1110 0011 0001 1111
0100 1111 0011 1100 1000 1100 1111 0111 1100 0000 1101 1101 0001 0011 0010 1110 0110 0000 0011
1111 0011 0011 0011 0000 0111 0000 1110 0100 0111 0010 0110 1100 0001 0000 0000 1110 1111 1111 0000 0000
1111 1100 0010 0111 0111 0011 1101 0110 1001 1010 0001 1011 0001 1000 0100 1001 1000 1000 1000
0110 1010 0001 1100 0100 1111 0100 1000 0010 0111 1110 1110 0100 0000 0011 1111 0011 1111 0011 1110
0000 1000 0110 0000 1111 1100 1111 0010 0110 0011 0000 0001 1100 0010 1111 1011 1111 0001 1001 1101 1000
0000 1110 0110 0111 0011 1100 0001 0000 0110 0011 0000 0111 0010 1100 1100 1000 0101 1000 0111 1111 0110
1110 1001 0111 0011 1000 1101 0010 0000 1000 1011 1100 1110 0010 0001 1100 0000 0100 0010 1111 0011 1001
0011 0110 0111 0110 1011 1001 0100 1111 0001 1111 1111 0010 0011 0111 0011 0010 1110 0000 1110 1011 0000
0110 0100 1100 0001 0110 1100 1000 1001 1101 0110 1111 1111 1000 1001 0011 0111 1111 0001 0110 0110 0110
1011 0001 0111 1001 1100 0110 1100 1000 0010 0011 0001 1111 1011 1100 0001 1100 1111 1001 0111 0001
0110 0101 0110 0010 1001 1100 0001 1100 1110 0010 1111 1000 0110 0011 1100 0011 0001 1000 1001 1011 0111
1111 0011 1000 1000 1101 1111 0000 0010 1111 1111 0000 0110 0000 0010 1110 0110 0000 1010 0011 0110 1110
1001 1111 1010 0111 1011 1100 1100 0000 0000 1011 0010 0011 0111 0000 1011 0100 0011 1000 0000 0000
```

Prof. Giovanni Mettivier

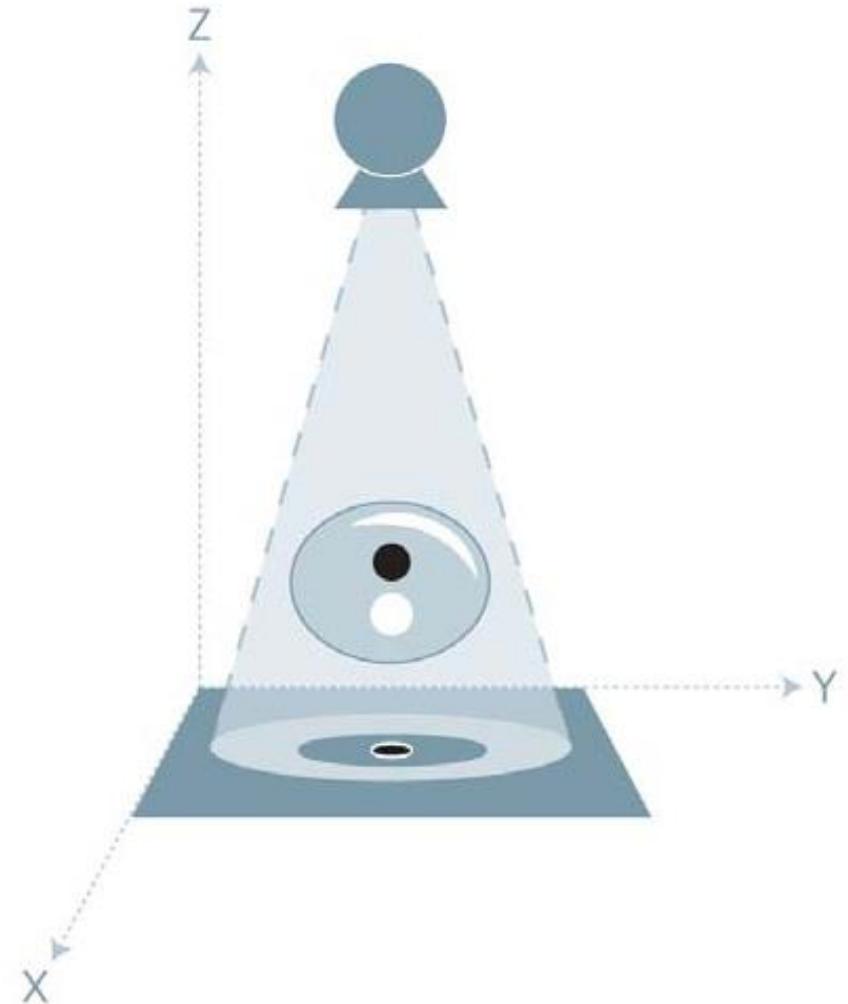
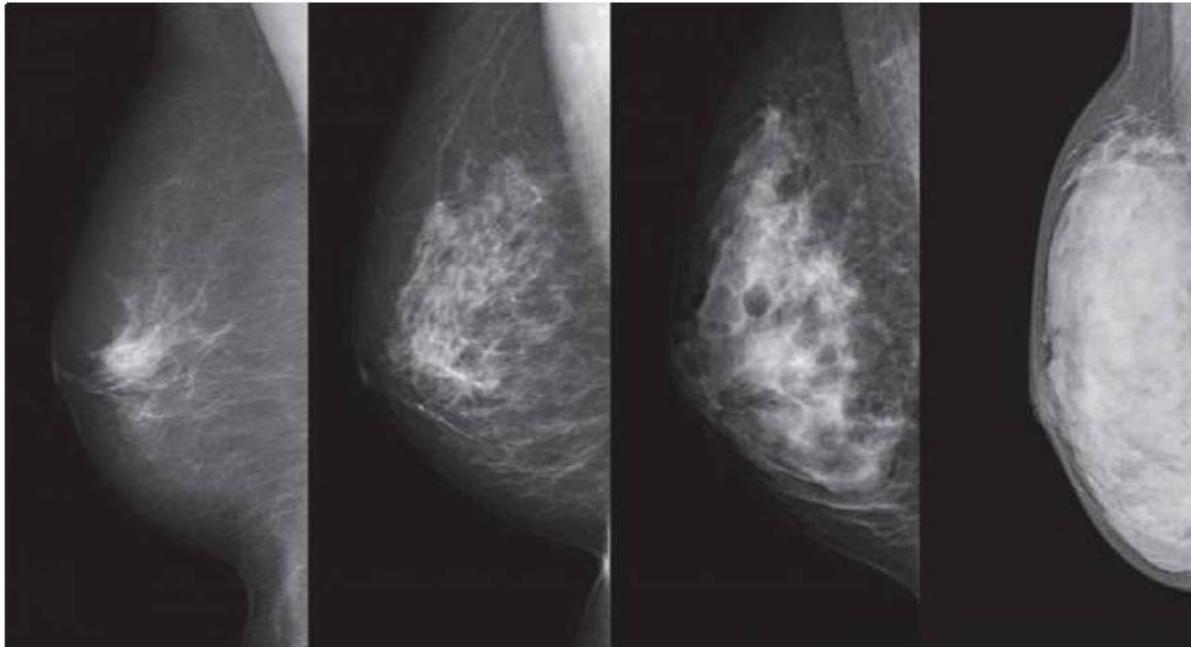






“However, due to the two-dimensional nature of projection imaging, mammography is limited by overlapping tissue

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



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

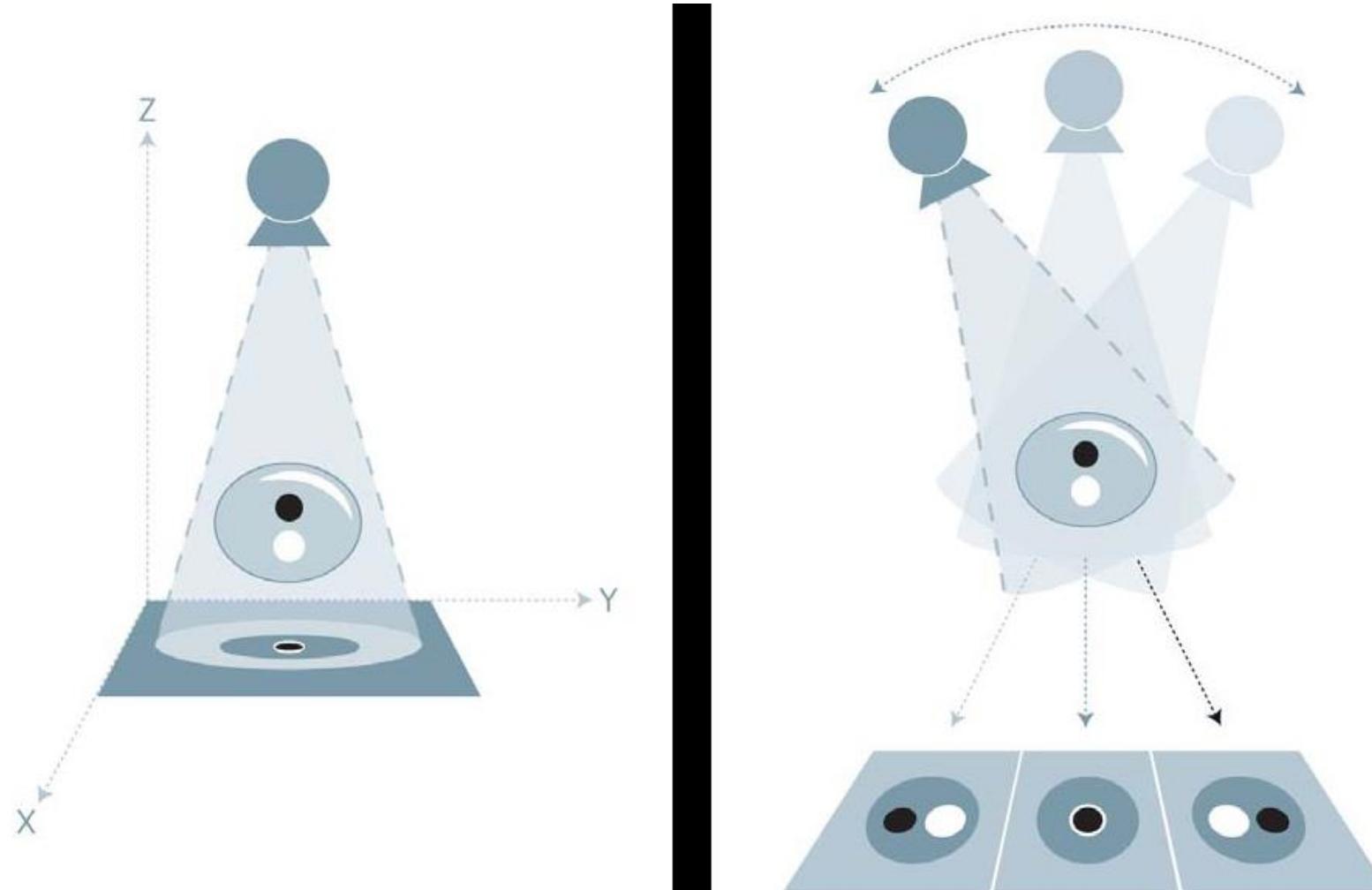
A. Hebecker, T. Mertelmeier & J. Orman, Siemens Medical Solutions, Erlangen, Germany





M P R L
Medical Physics Research Laboratory

Digital Breast Tomosynthesis



www.siemens.com/healthcare



University of Naples "Federico II"- Physics Department "Ettore Pancini"
National Institute of Nuclear Physics

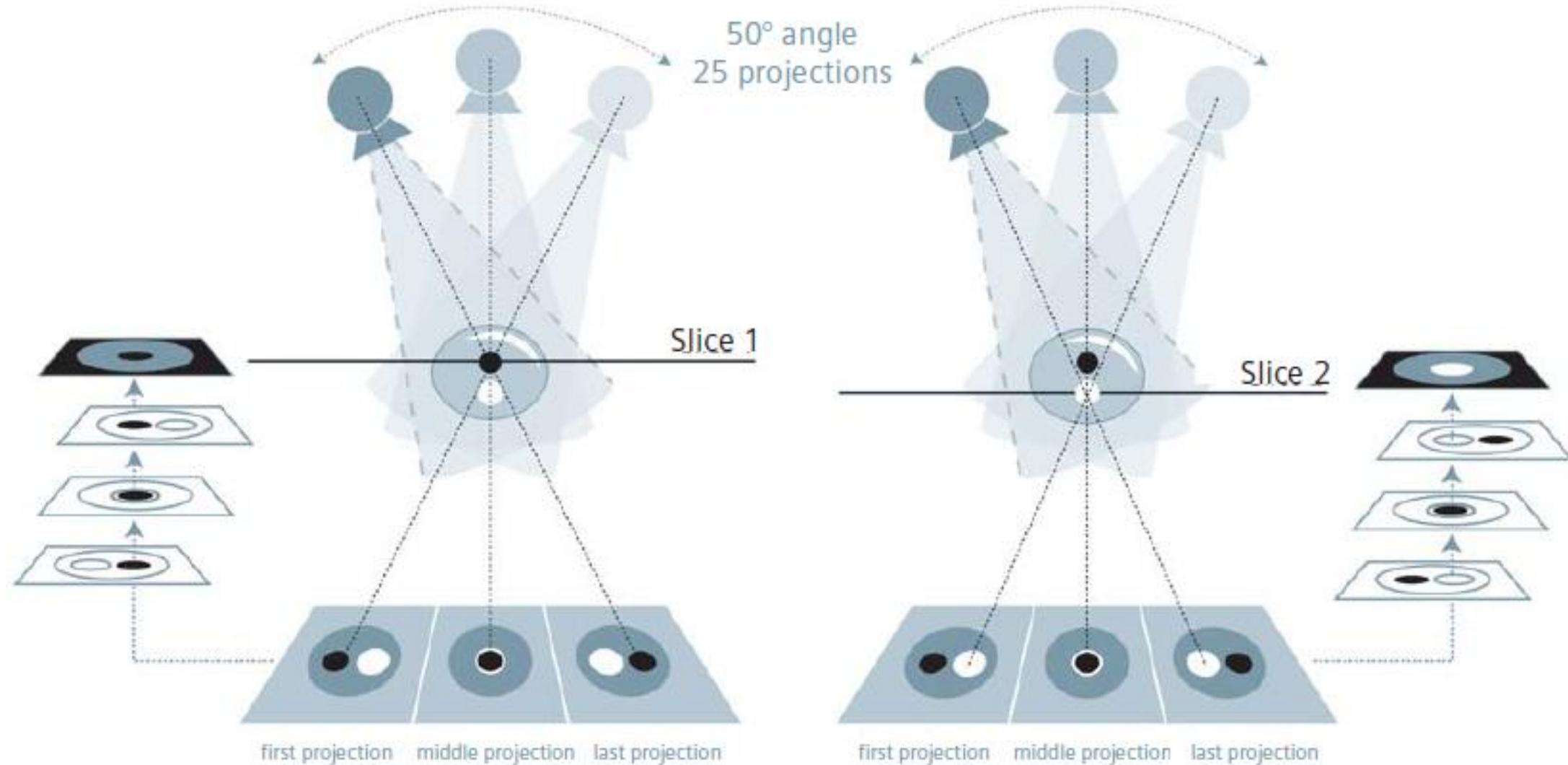
INFN
Istituto Nazionale di Fisica Nucleare



M P R L
Medical Physics Research Laboratory

Digital Breast Tomosynthesis

3D Breast Tomosynthesis –
White Paper – www.siemens.com/healthcare



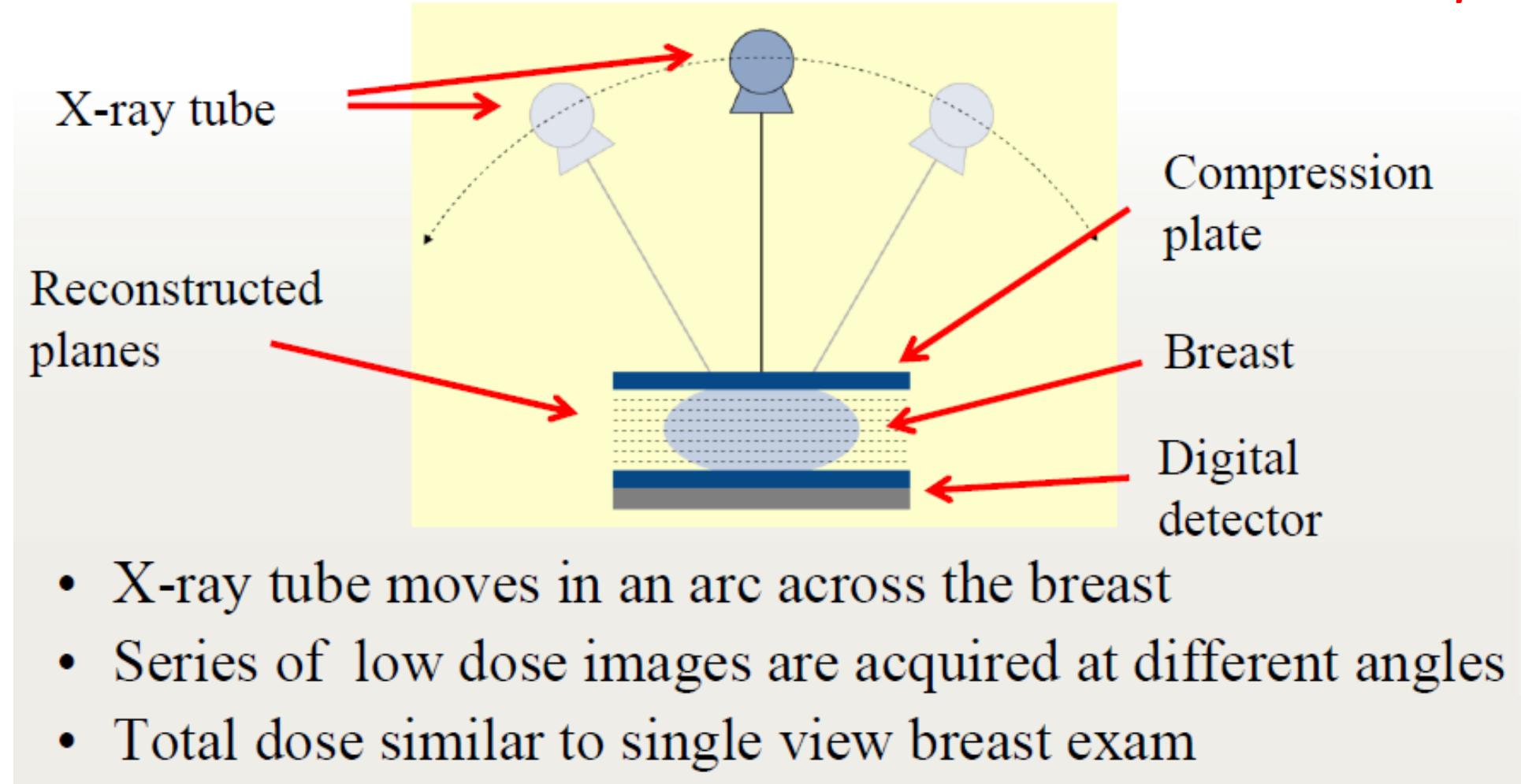
University of Naples "Federico II" - Physics Department "Ettore Pancini"
National Institute of Nuclear Physics

INFN
Istituto Nazionale di Fisica Nucleare

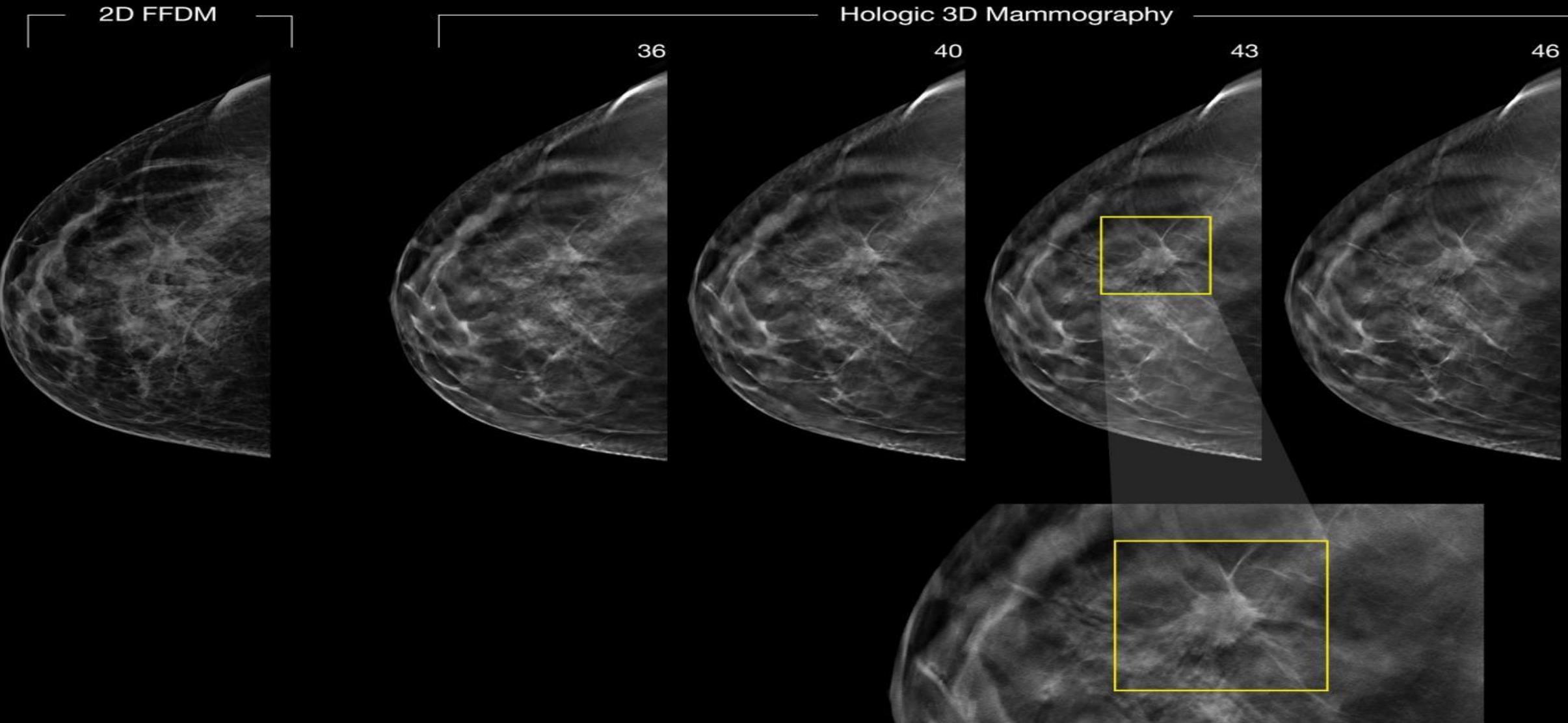


Digital Breast Tomosynthesis

Acquisition



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

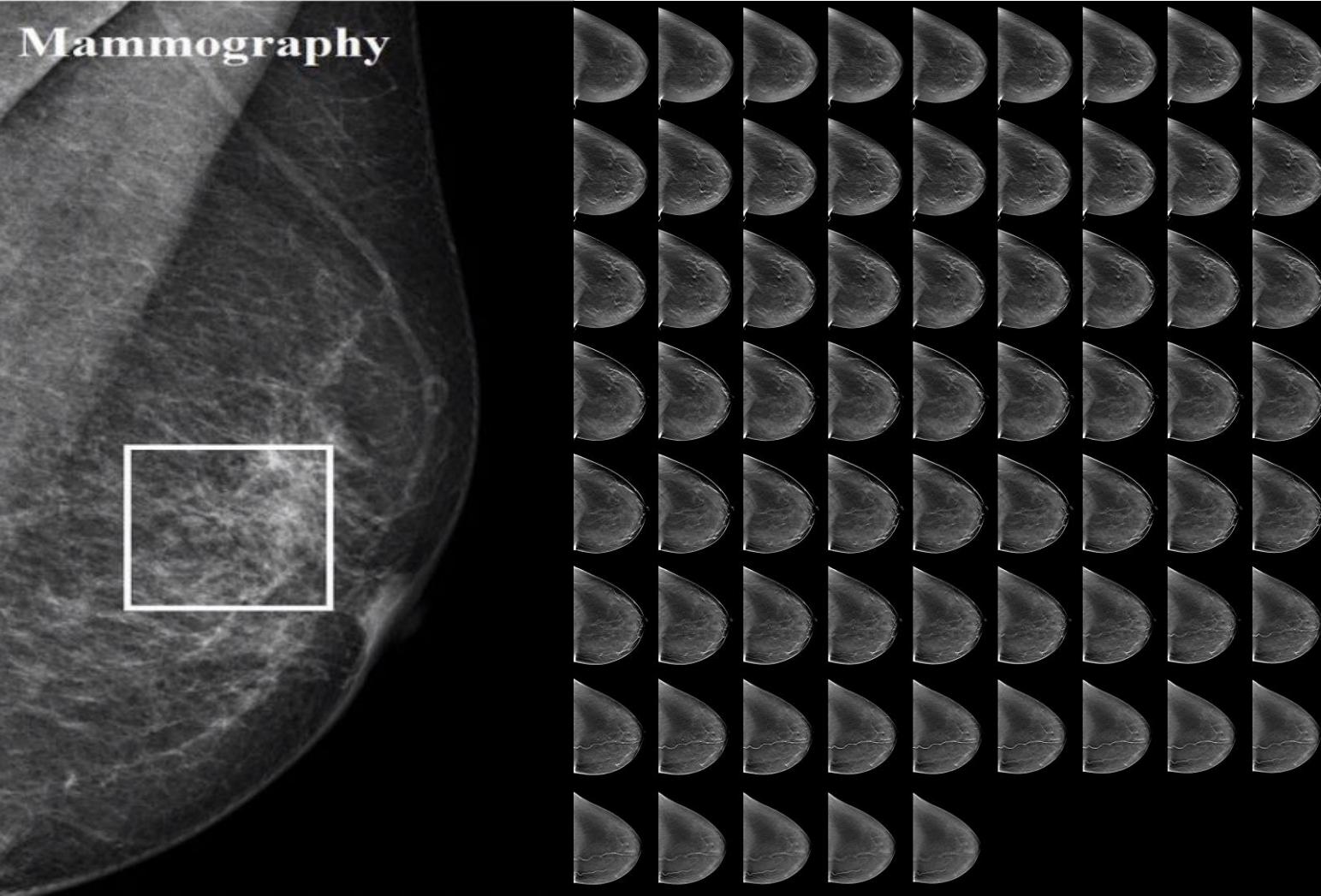




M P R L
Medical Physics Research Laboratory

PROBLEMATICHE

Mammography



Maggior numero di immagini da analizzare

Maggior carico lavorativo per il medico radiologo

Maggiore probabilità di effettuare una diagnosi erronea o incompleta



University of Naples "Federico II"- Physics Department "Ettore Pancini"
National Institute of Nuclear Physics

INFN
Istituto Nazionale di Fisica Nucleare



Classificazione delle DBT

Meno stress
lavorativo a carico del
personale medico

Meno stress
psicologico ai pazienti

Riduzione dei costi
per le aziende
ospedaliere

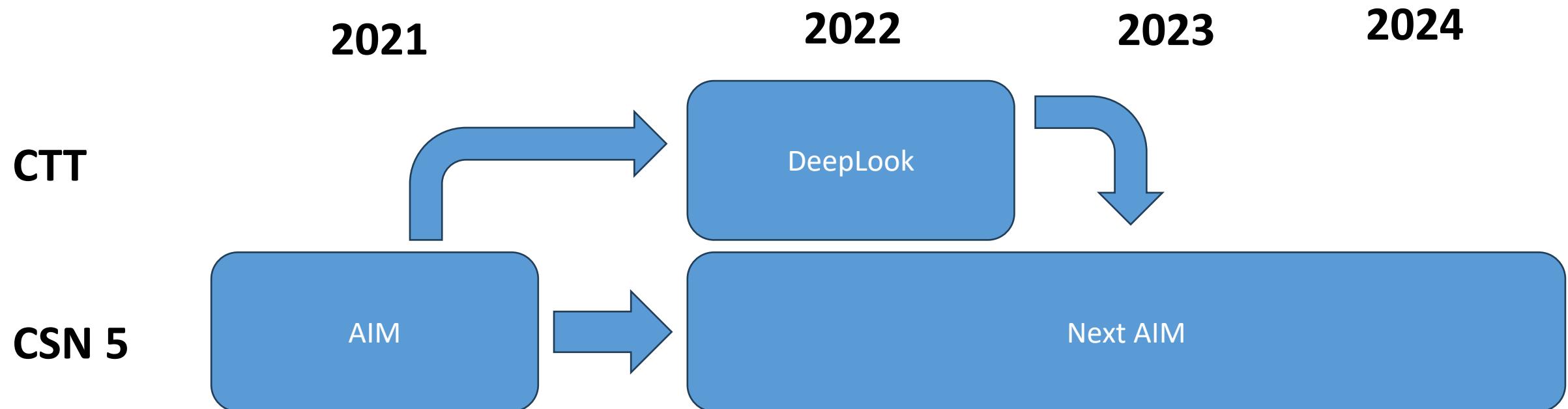
McDonald RJ et al, "The effects of changes in utilization and technological advancements of cross-sectional imaging on radiologist workload." Acad Radiol. Sep;22(9):1191-8 (2015).





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.





M P R L
Medical Physics Research Laboratory



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

ALMA MATER STUDIORUM
UNIVERSITÀ DI BOLOGNA

ASL CUNEO 1

M. Porzio



AORN Cardarelli

S. Minelli, E. Antignani, A. Santoro



IFO Regina Elena

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



University of Naples "Federico II"- Physics Department "Ettore Pancini"
National Institute of Nuclear Physics





M P R L
Medical Physics Research Laboratory

DeepLook Dataset

Dataset (Hospital site)	Expected final no. of patients	Present no. of patients	Total no. DBT slices	TP	TN	Bio	DBT scanner	View	FFDM availab le
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				



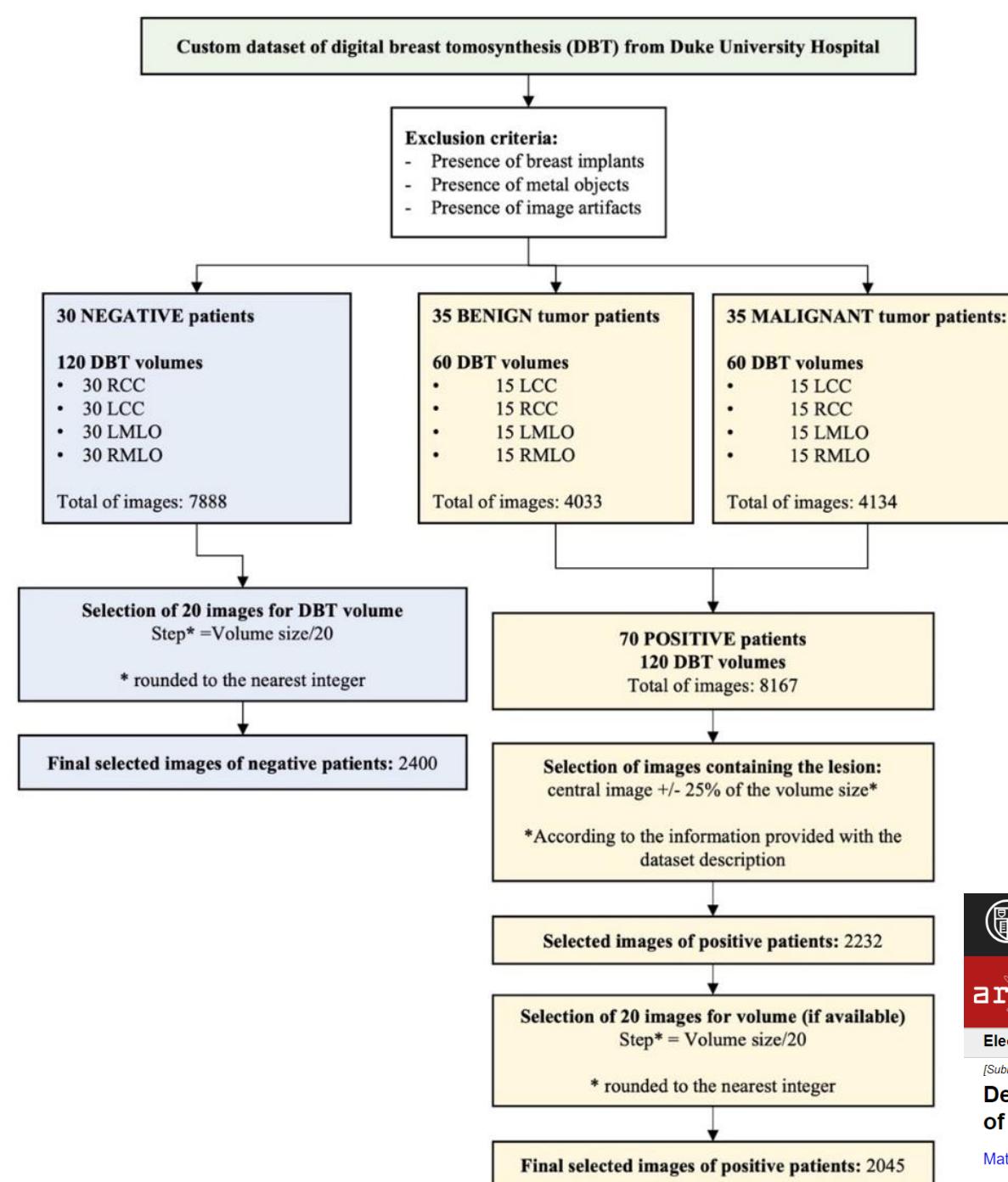
All the images were annotated by dedicated breast radiologists



University of Naples "Federico II"- Physics Department "Ettore Pancini"
National Institute of Nuclear Physics



Duke Dataset



JAMA Network®

JAMA Network Open | Enter Search Term

This Issue | Views 18,927 | Citations 37 | Altmetric 30

Download PDF | More | Cite This | Permissions

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

Search... Help | About

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 Świecicki, 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



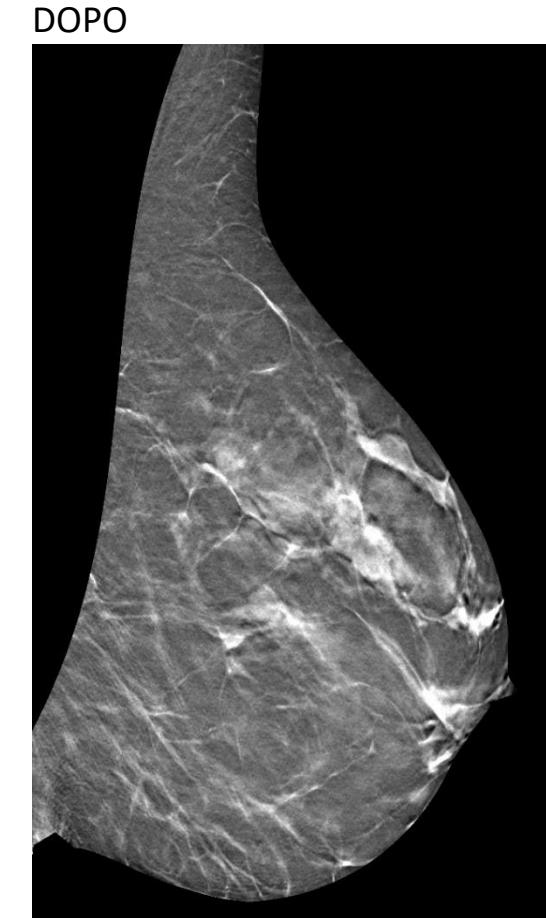


Preprocessing delle immagini

Importantissimo il lavoro fatto con le GradCAM

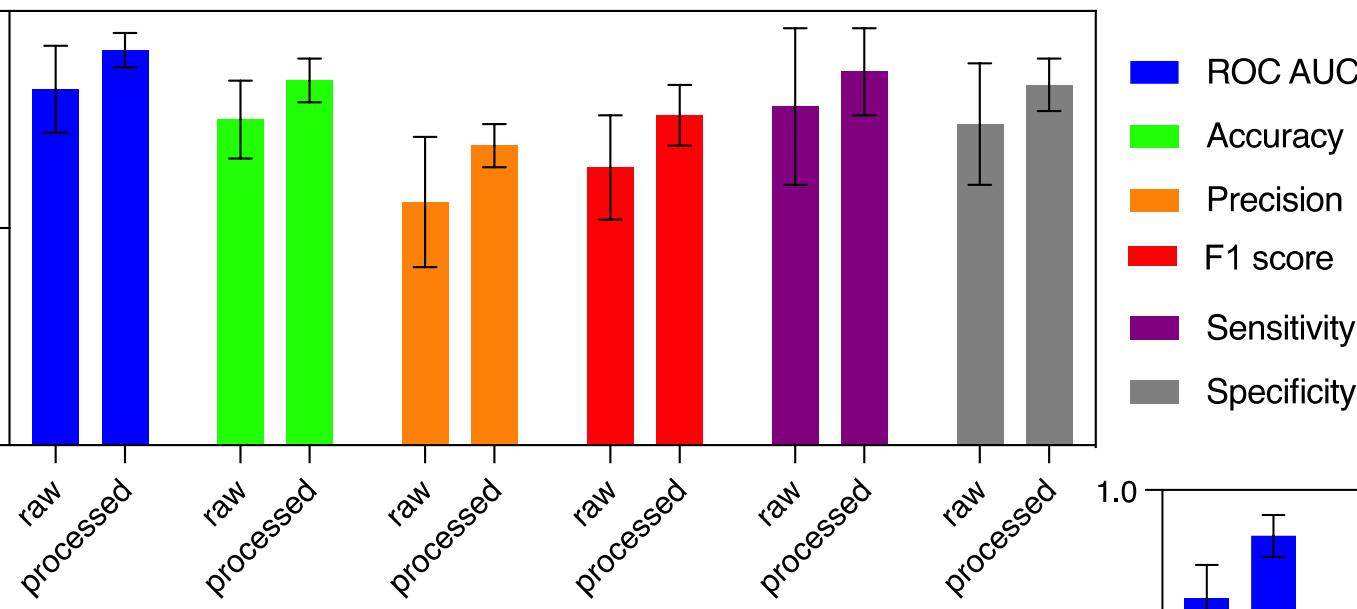


- Step 1 Riduzione del rumore
- Step 2 Incremento del contrasto
- Step 3 Eliminazione automatica:
 - della pelle
 - del capezzolo
 - di ulteriori artefatti
 - del muscolo pettorale ove presente (MLO vista)
- Step 4 Binning automatico delle slices a 300 x 300 px



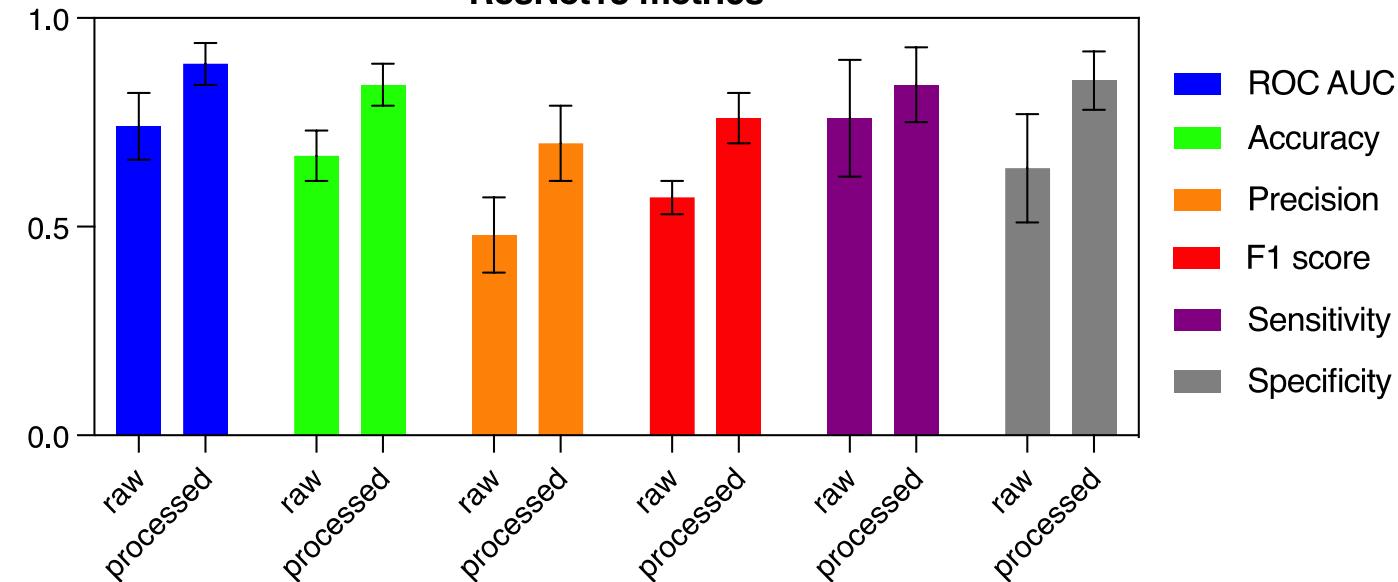


VGG16 metrics



Duke Dataset

ResNet18 metrics





Classification procedure

Step 1

Image
Pre-processing



Step 2

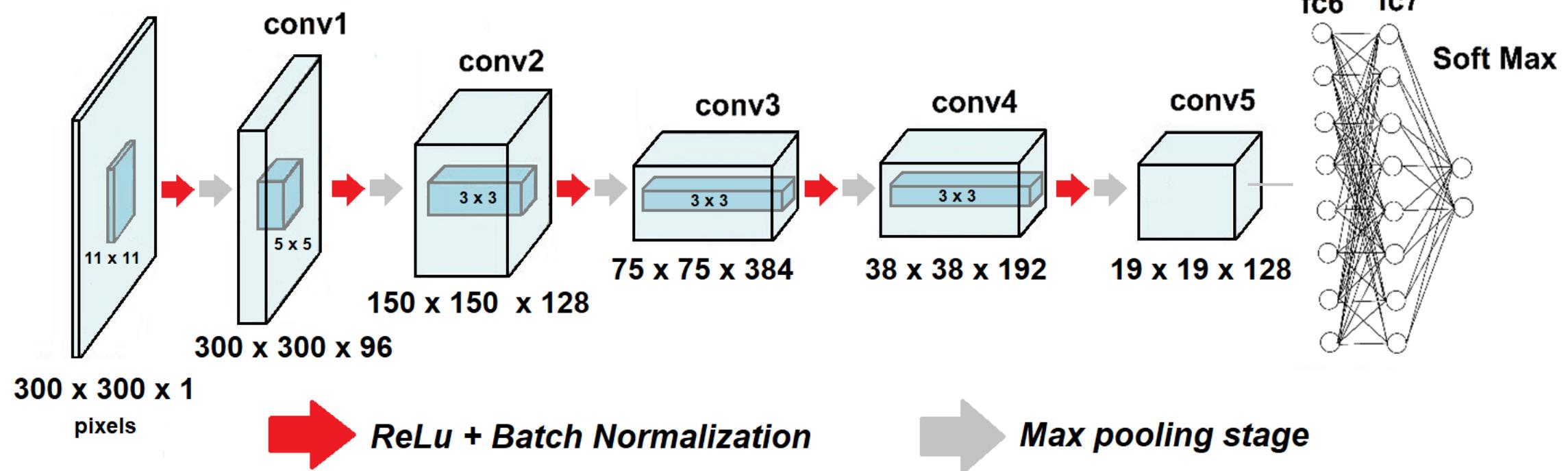
Slice
selection





Slice selection - network

Input Image

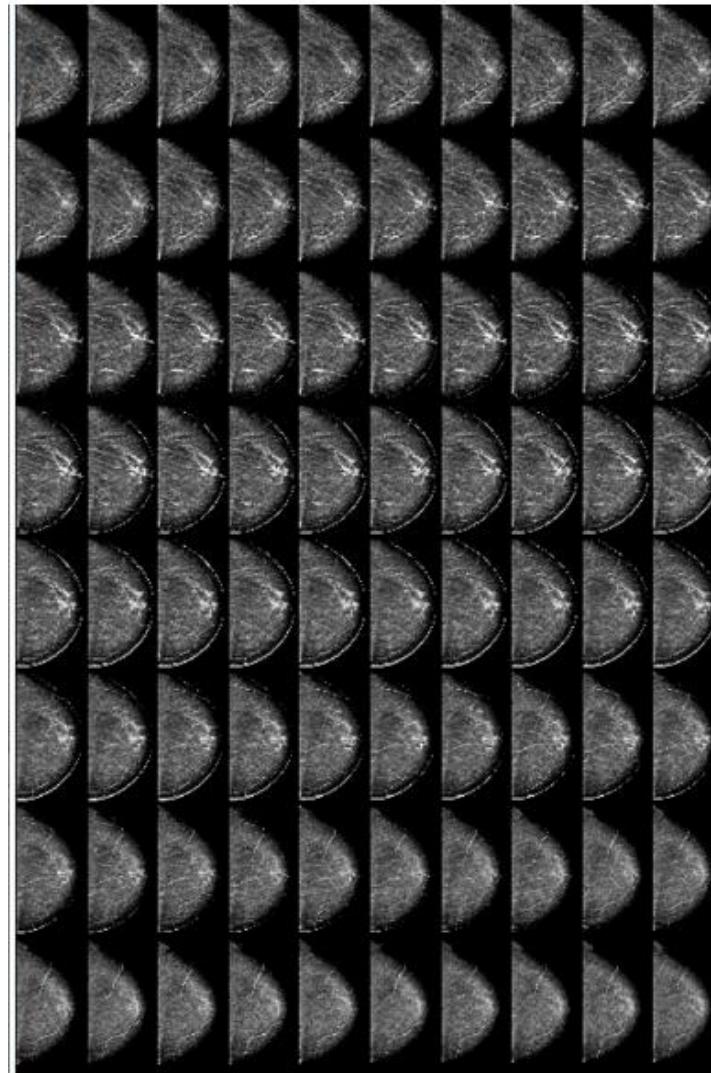


The DCNN-DBT was trained on a GPU NVIDIA GeForce RTX 3090 card (10496 CUDA cores, 24 GB GDDR6X video memory).

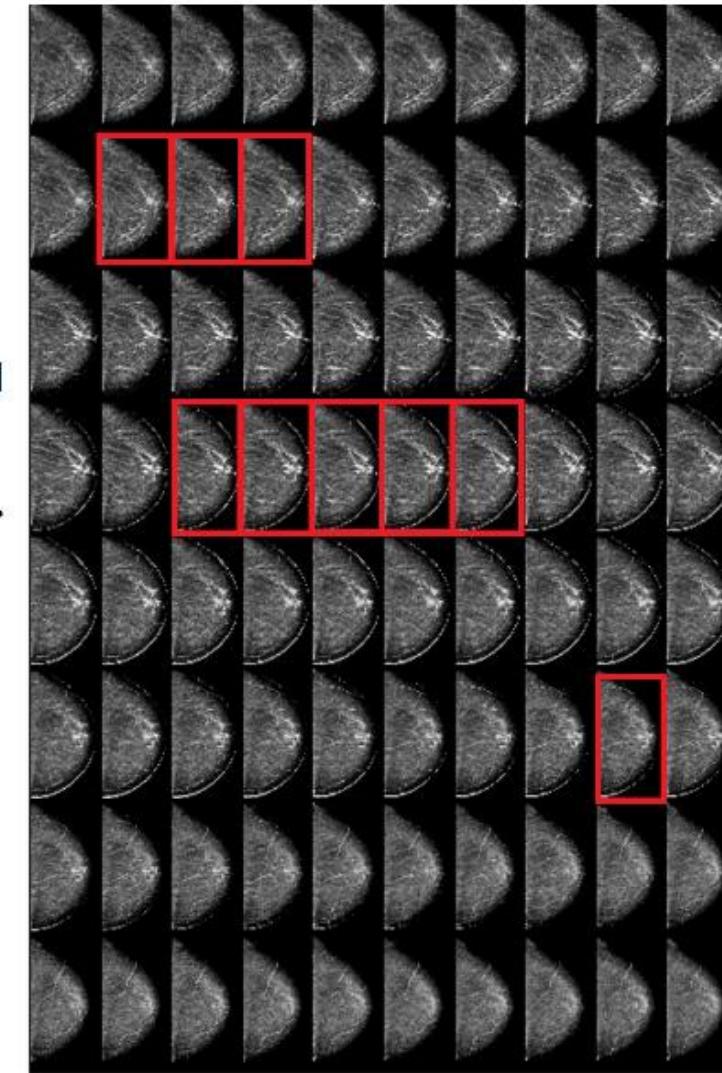
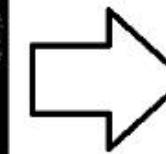




Patient 1 Dataset



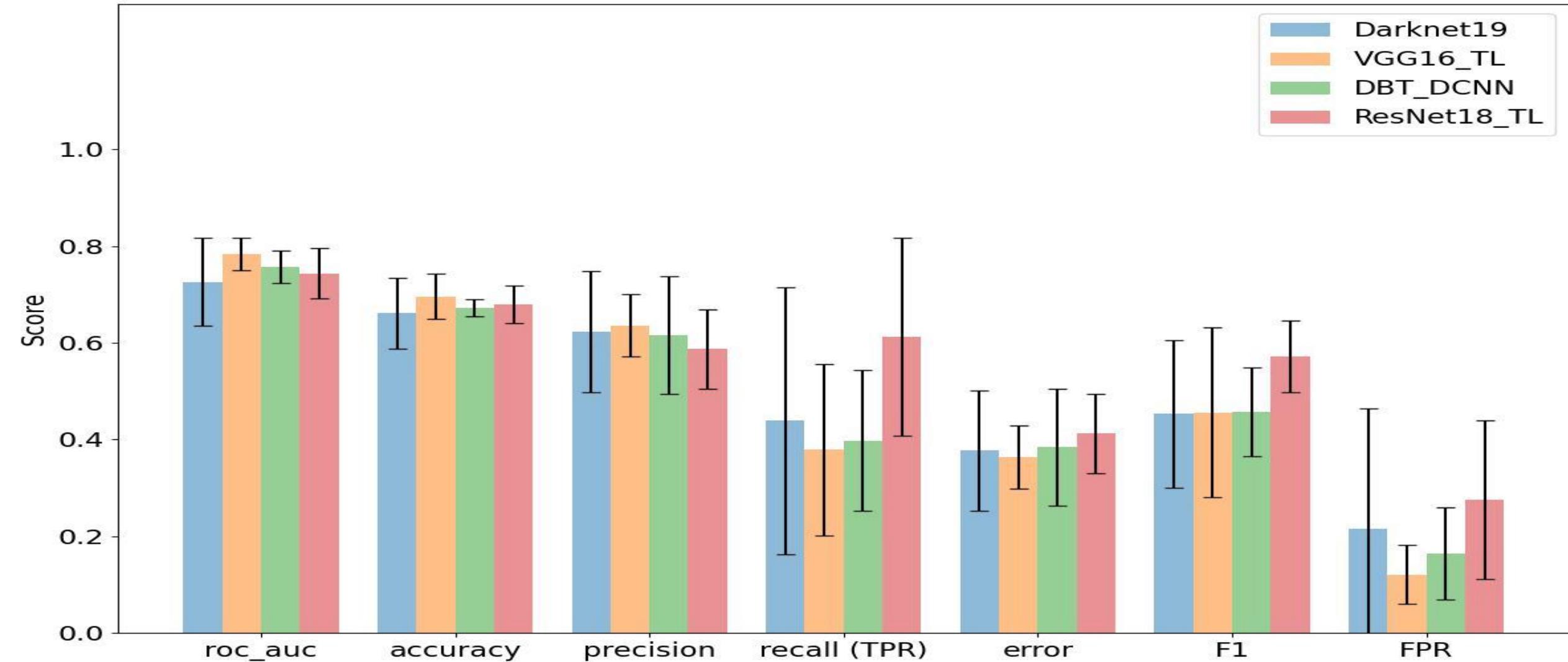
STAGE 1

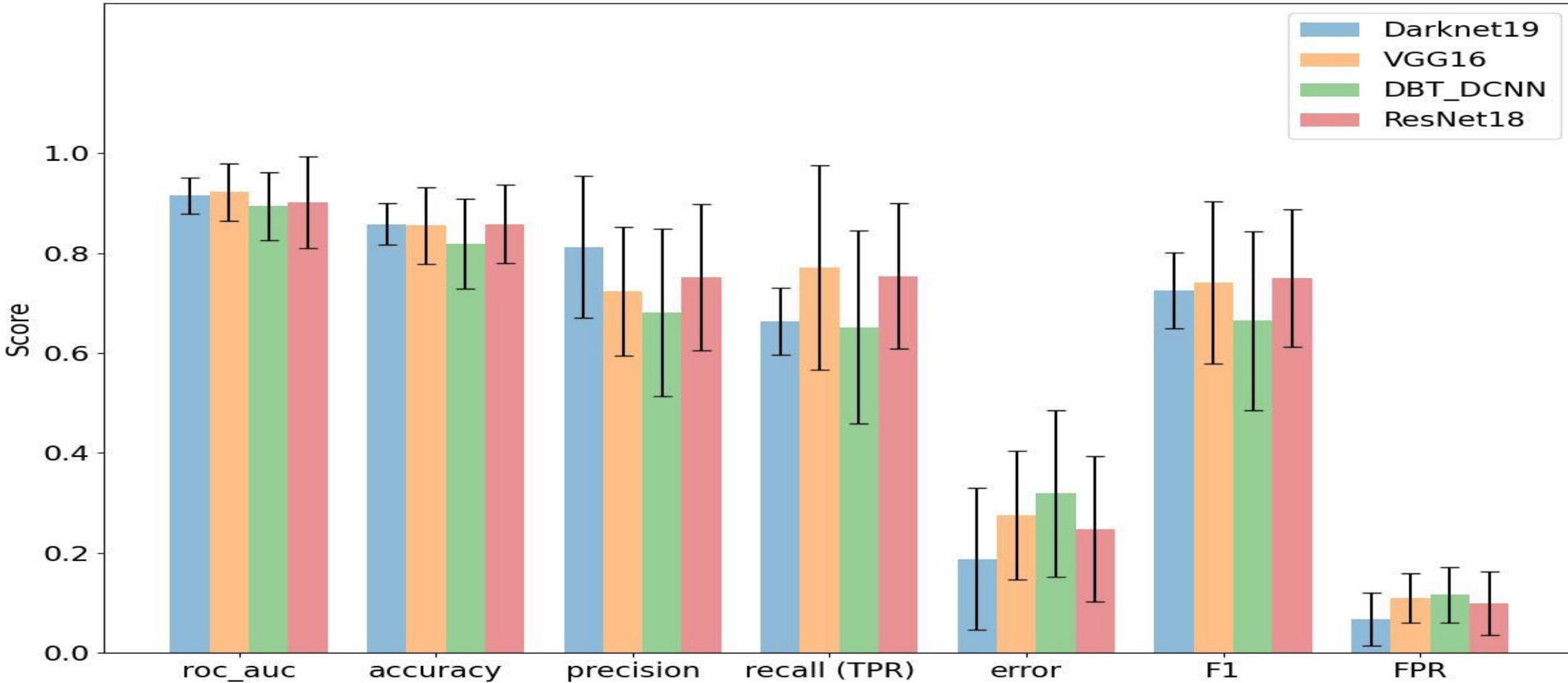




M P R L
Medical Physics Research Laboratory

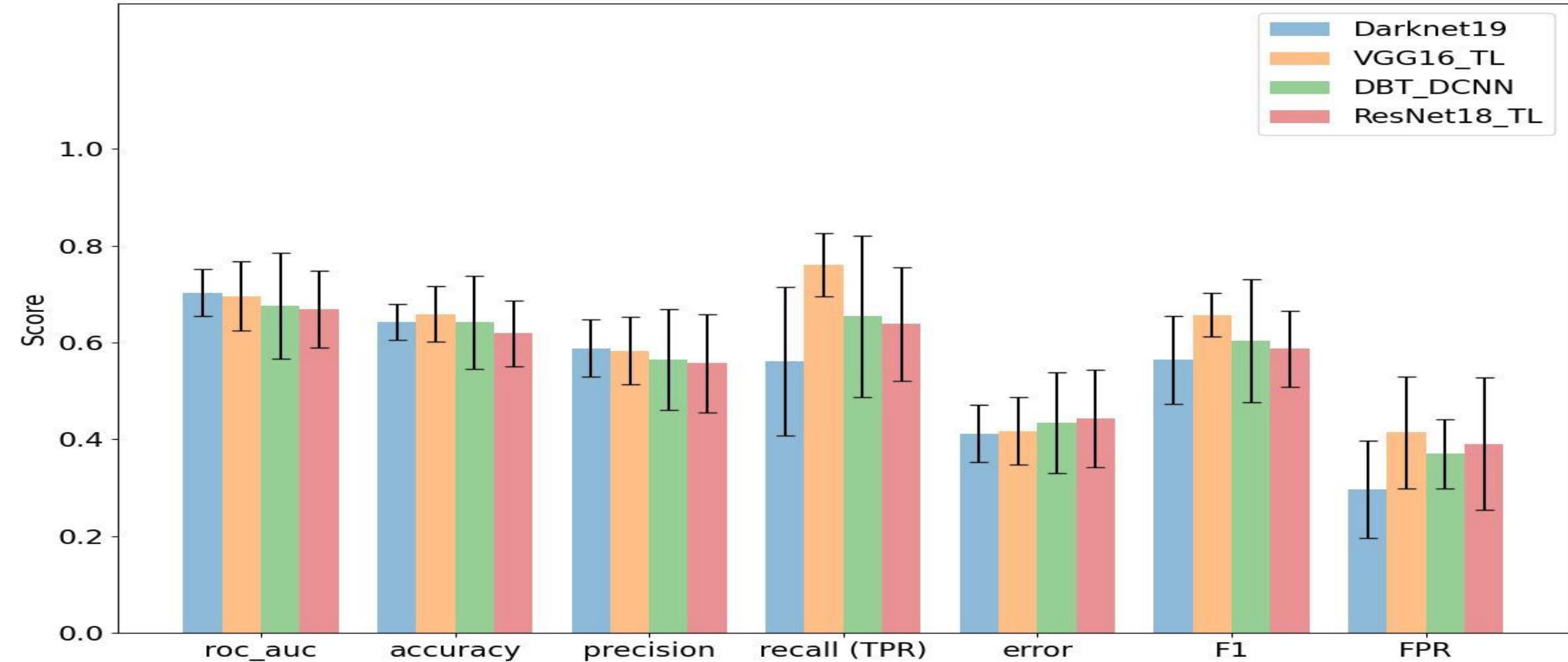
Metrics – Full Dataset

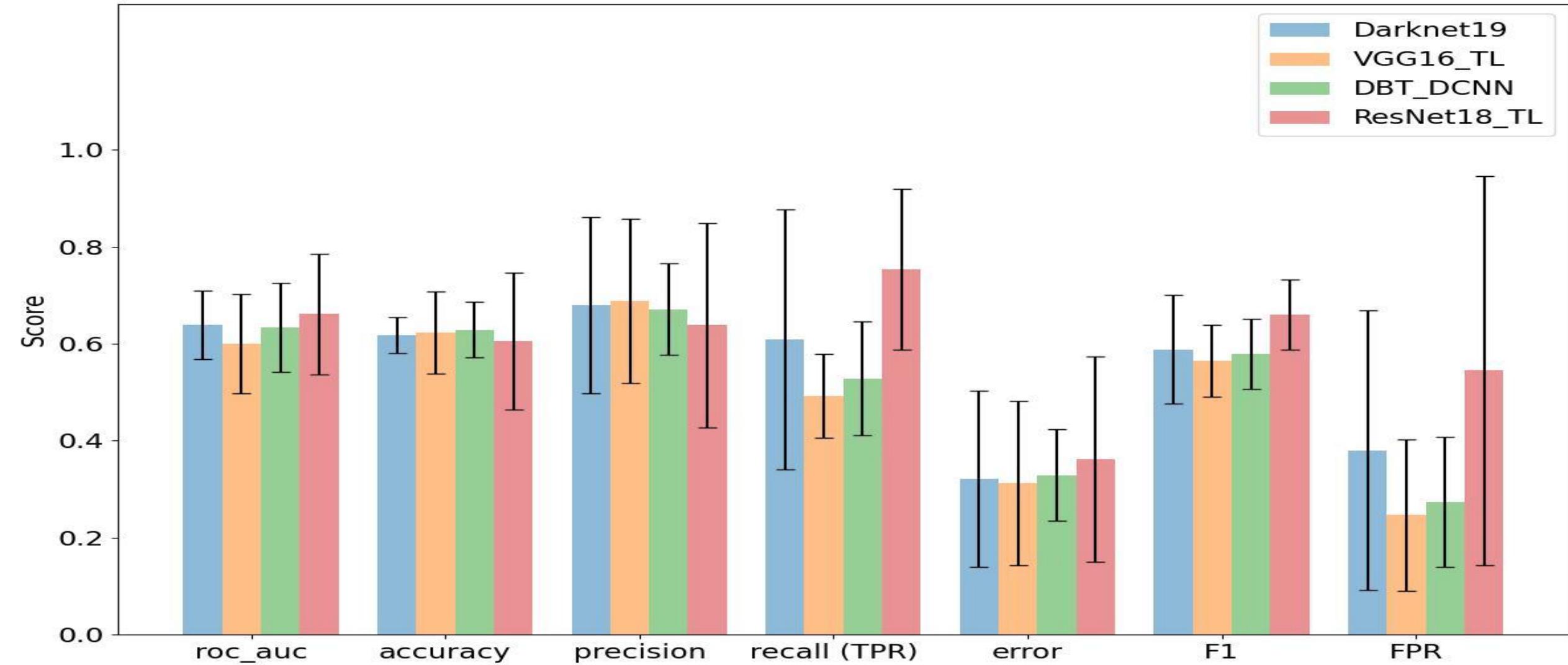


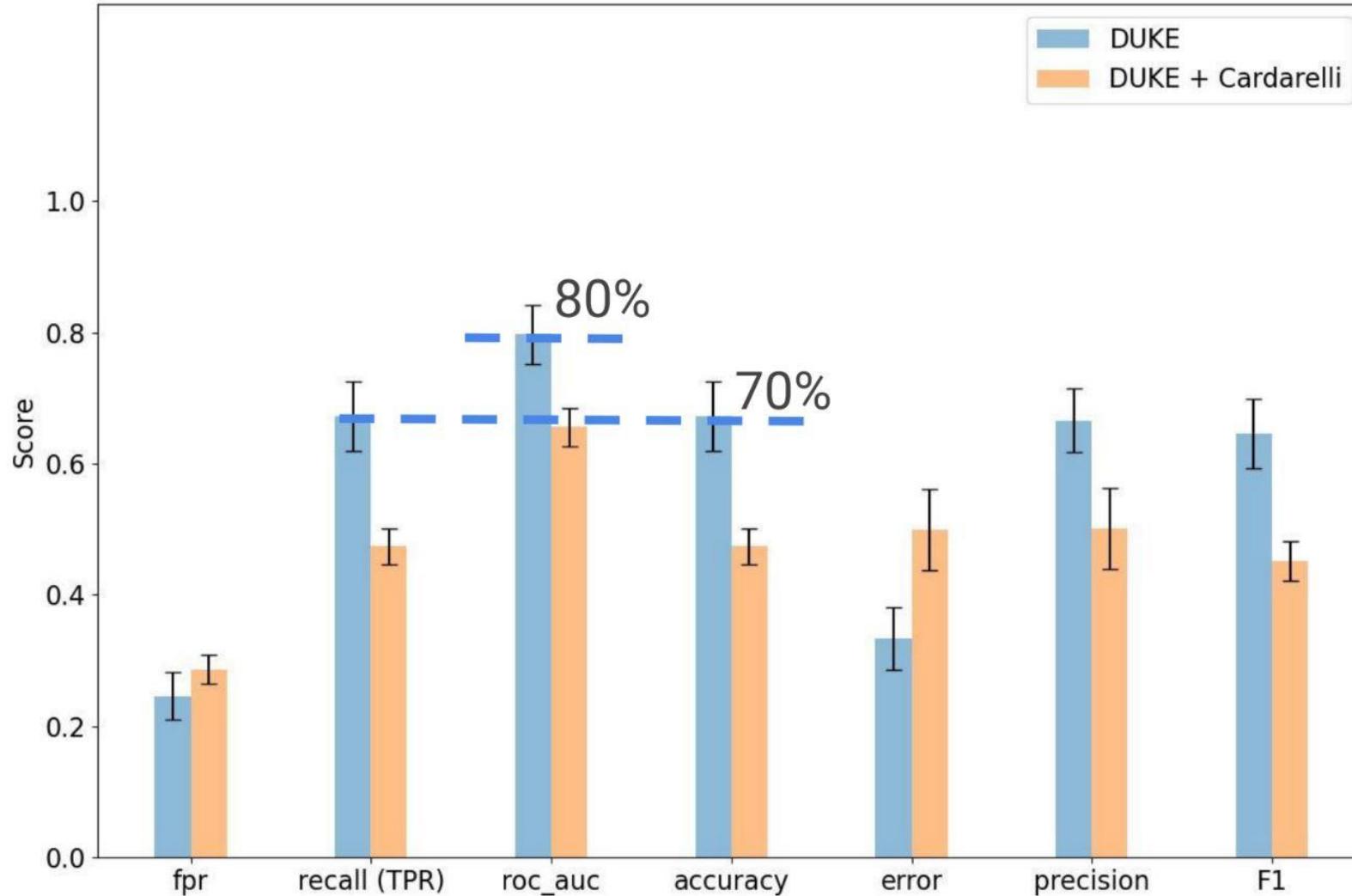




Metrics – Cardarelli Dataset







- Negative
- Benign masses
- Malignant masses



Classification procedure

Step 1

Image
Pre-processing



Step 2

Slice
selection



Step 3

Mass
localization

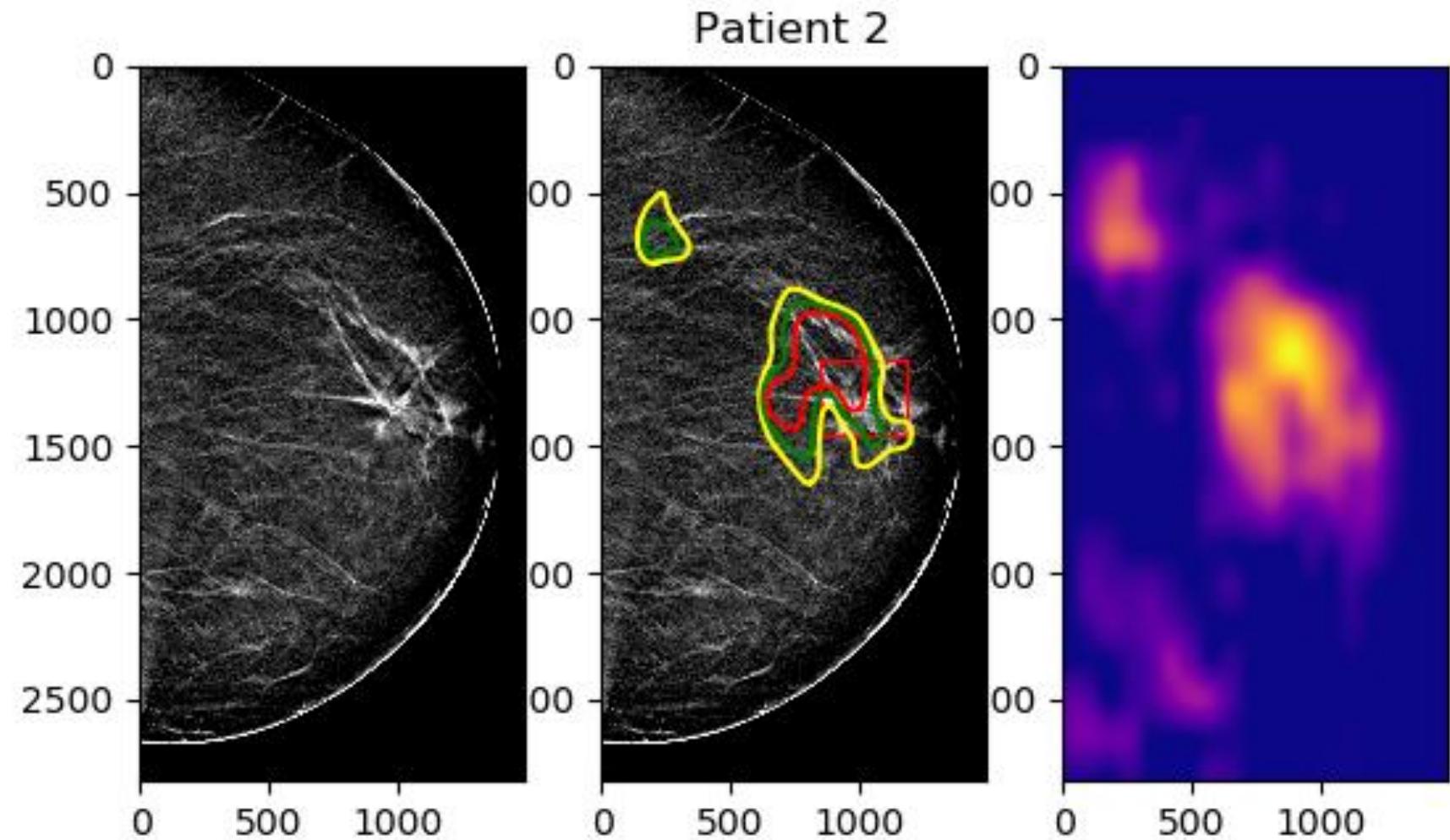




Mass Localization

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%





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

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

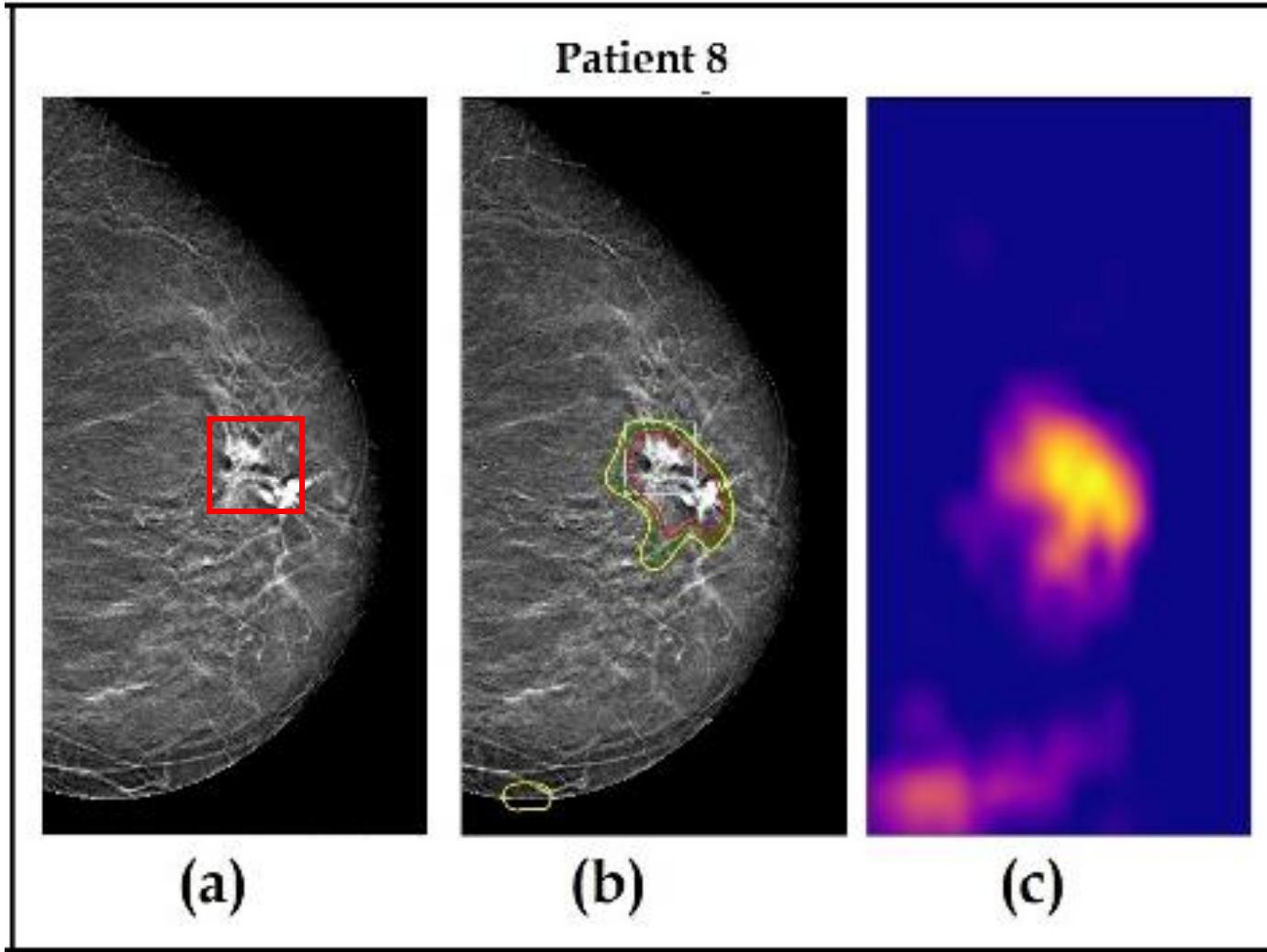
$$Activation = \frac{GradCAM\ ROI\ dim}{Image\ dim}$$

The ratio between the dimensions of GradCAM ROI and slice.





Mass Localization



— Threshold > 0.5

Overlap = 95%

Activation = 15%

— Threshold > 0.6

Overlap = 93%

Activation = 10%

— Threshold > 0.7

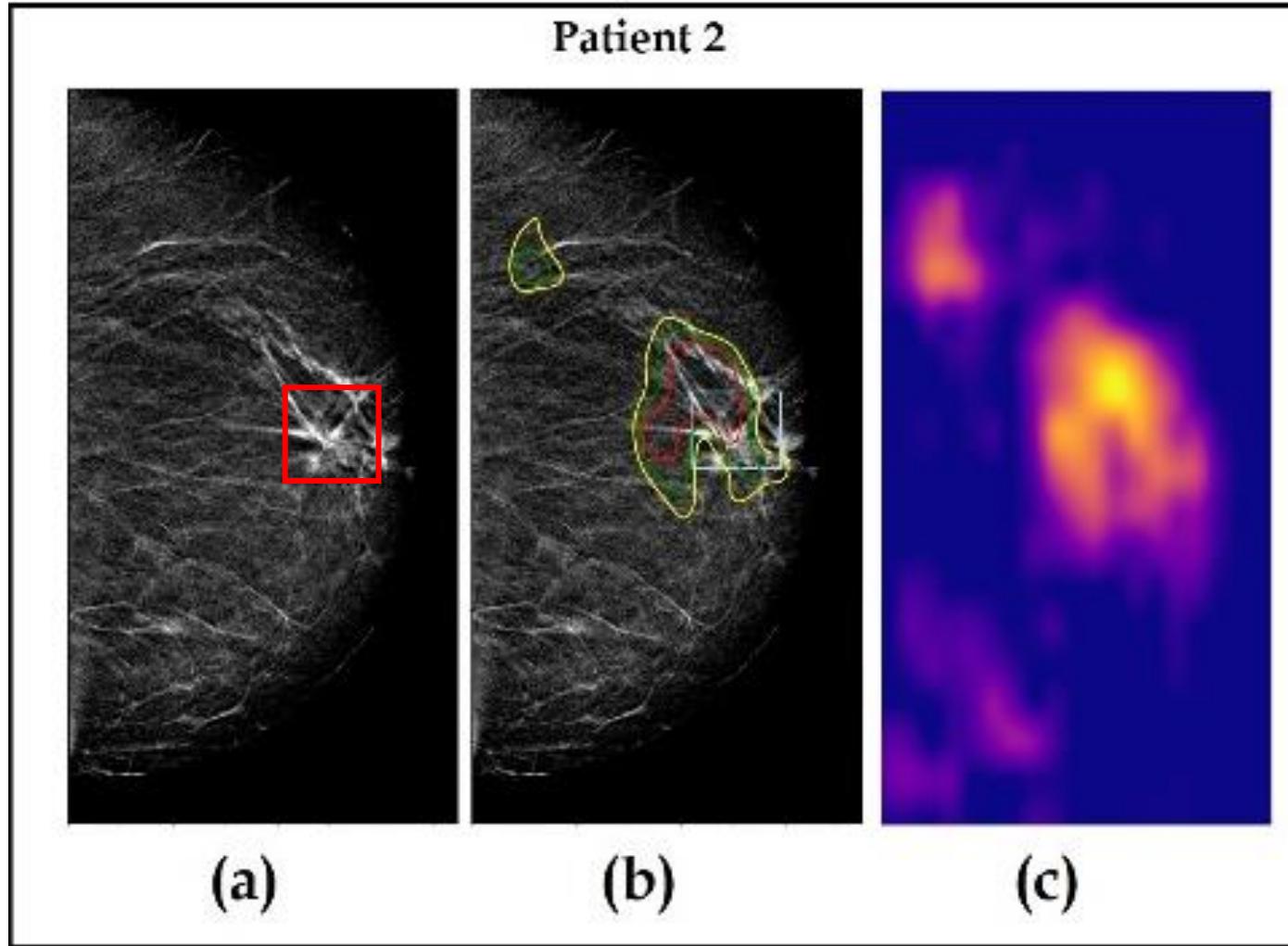
Overlap = 90%

Activation = 8%





Mass Localization



— Threshold > 0.5

Overlap = 75%

Activation = 25%

— Threshold > 0.6

Overlap = 60%

Activation = 15%

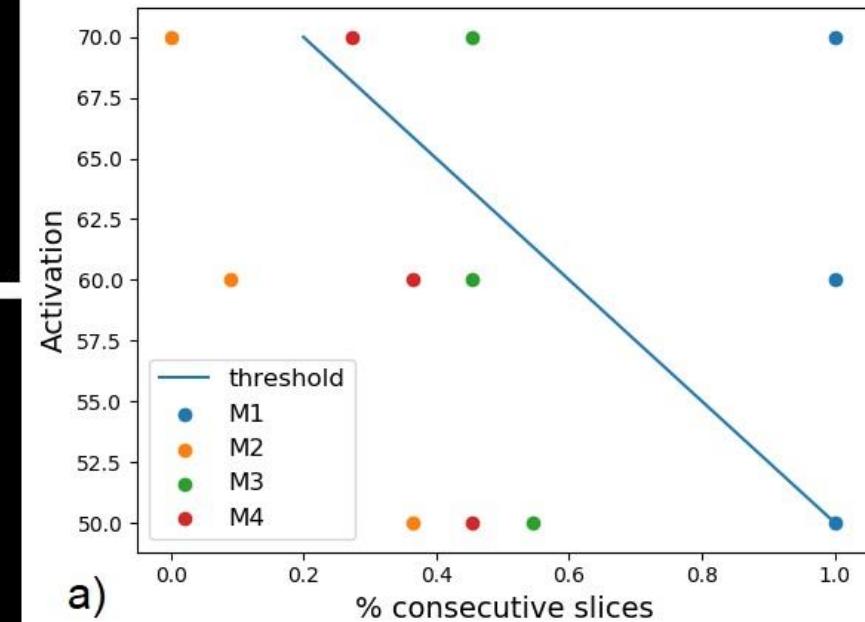
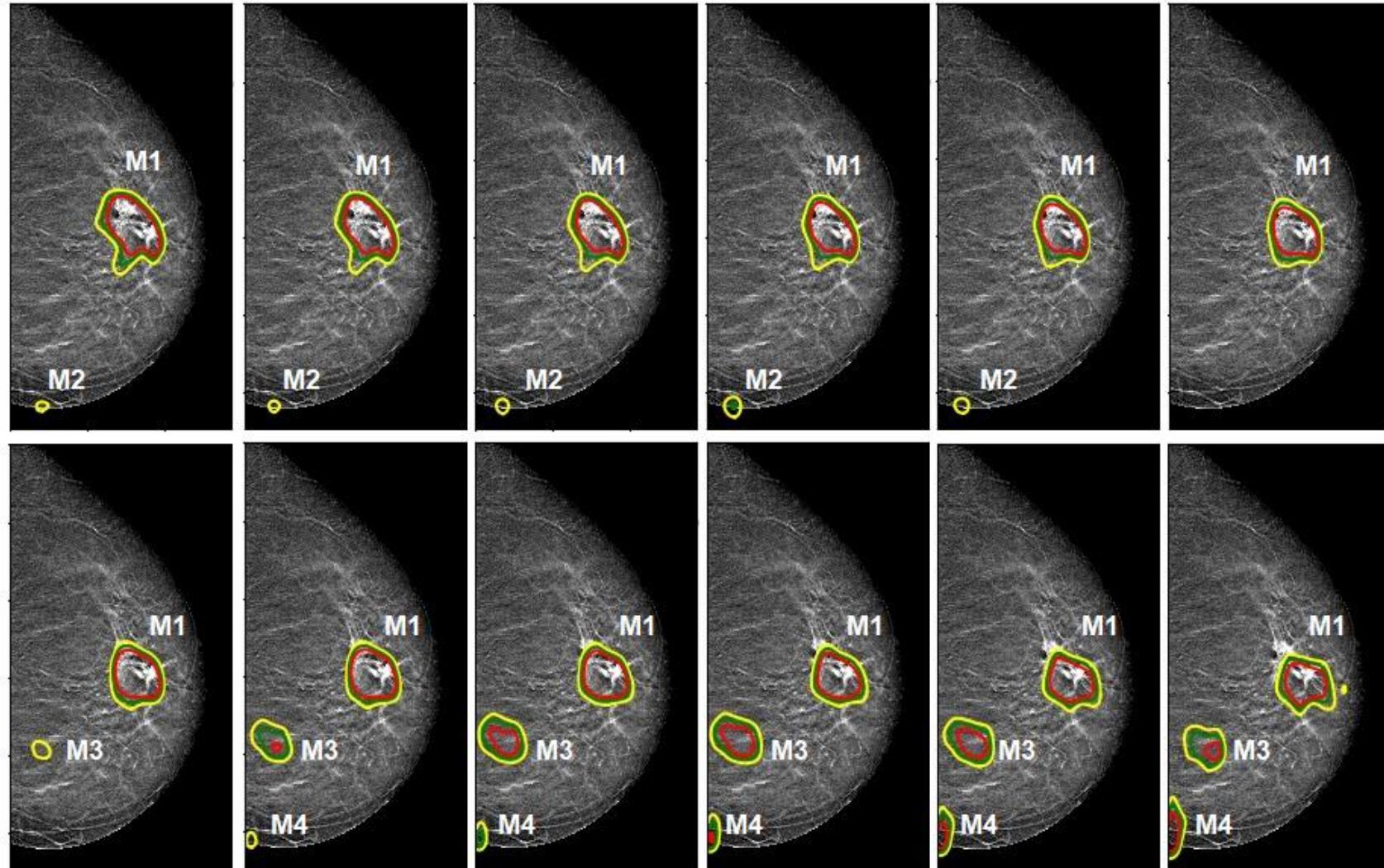
— Threshold > 0.7

Overlap = 45%

Activation = 10%

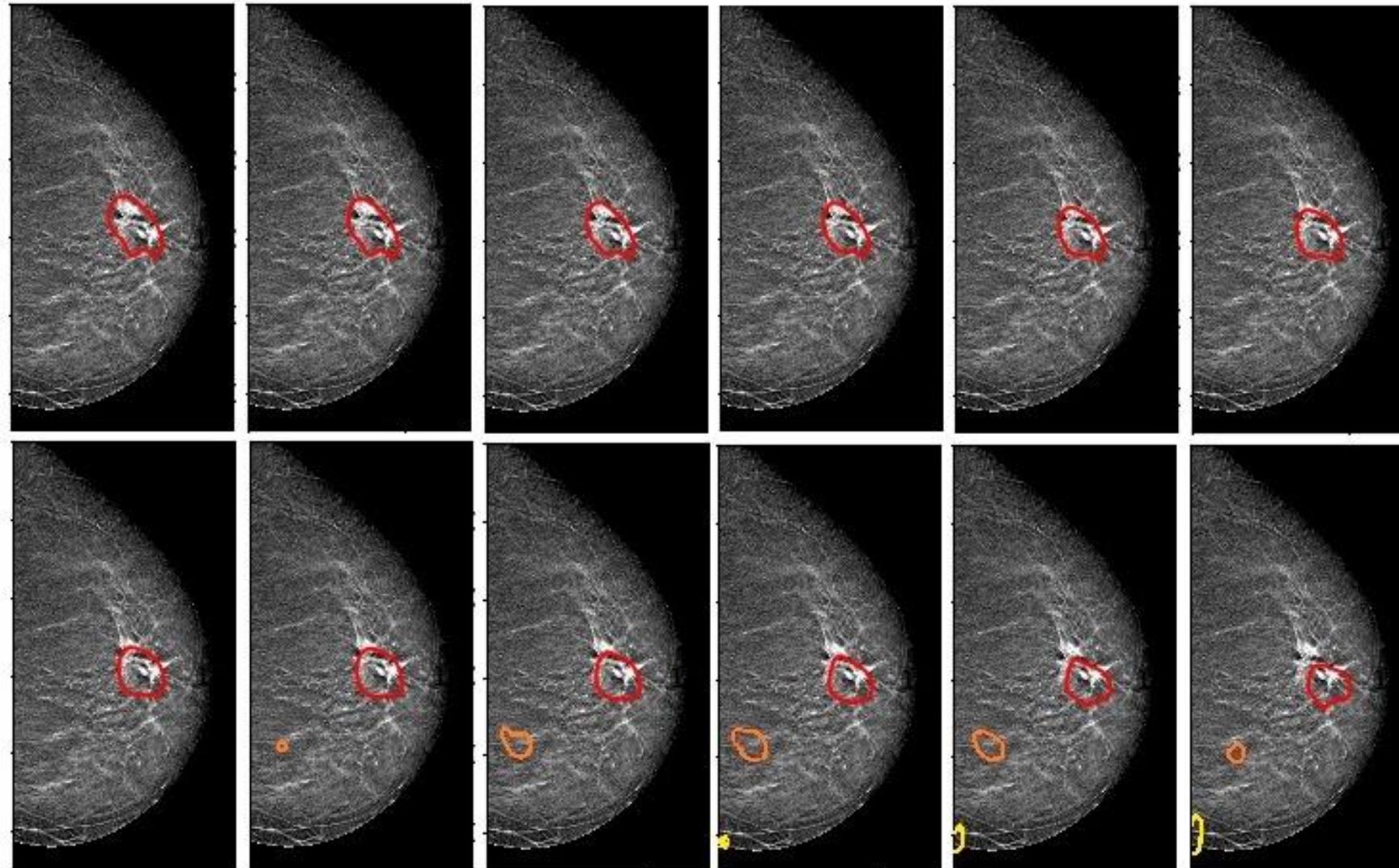


False positive reduction





Final result



Confidence Level

- Low
- Medium
- High





Classification procedure

Step 1

Image
Pre-processing

Step 2

Slice
selection

Step 3

Mass
localization

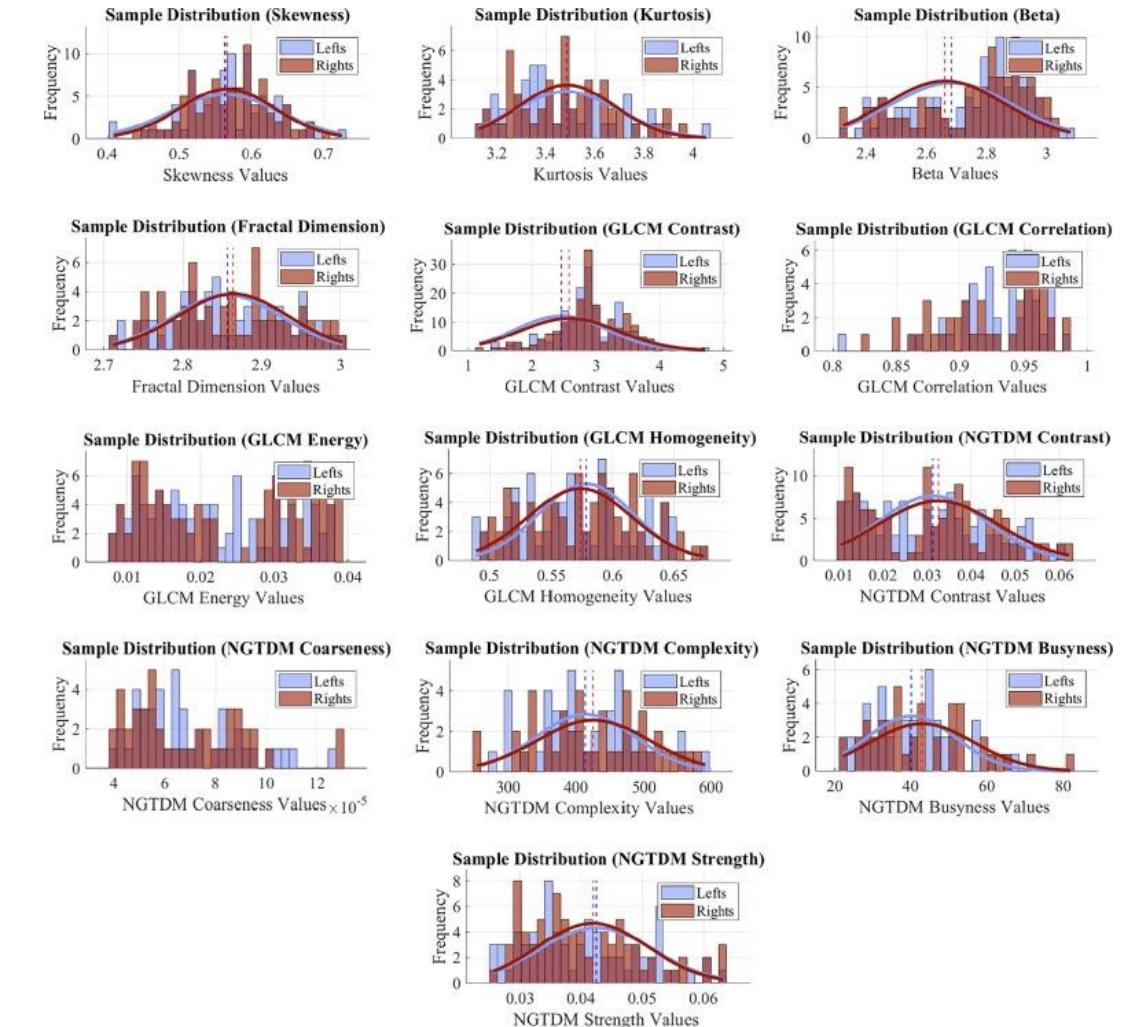
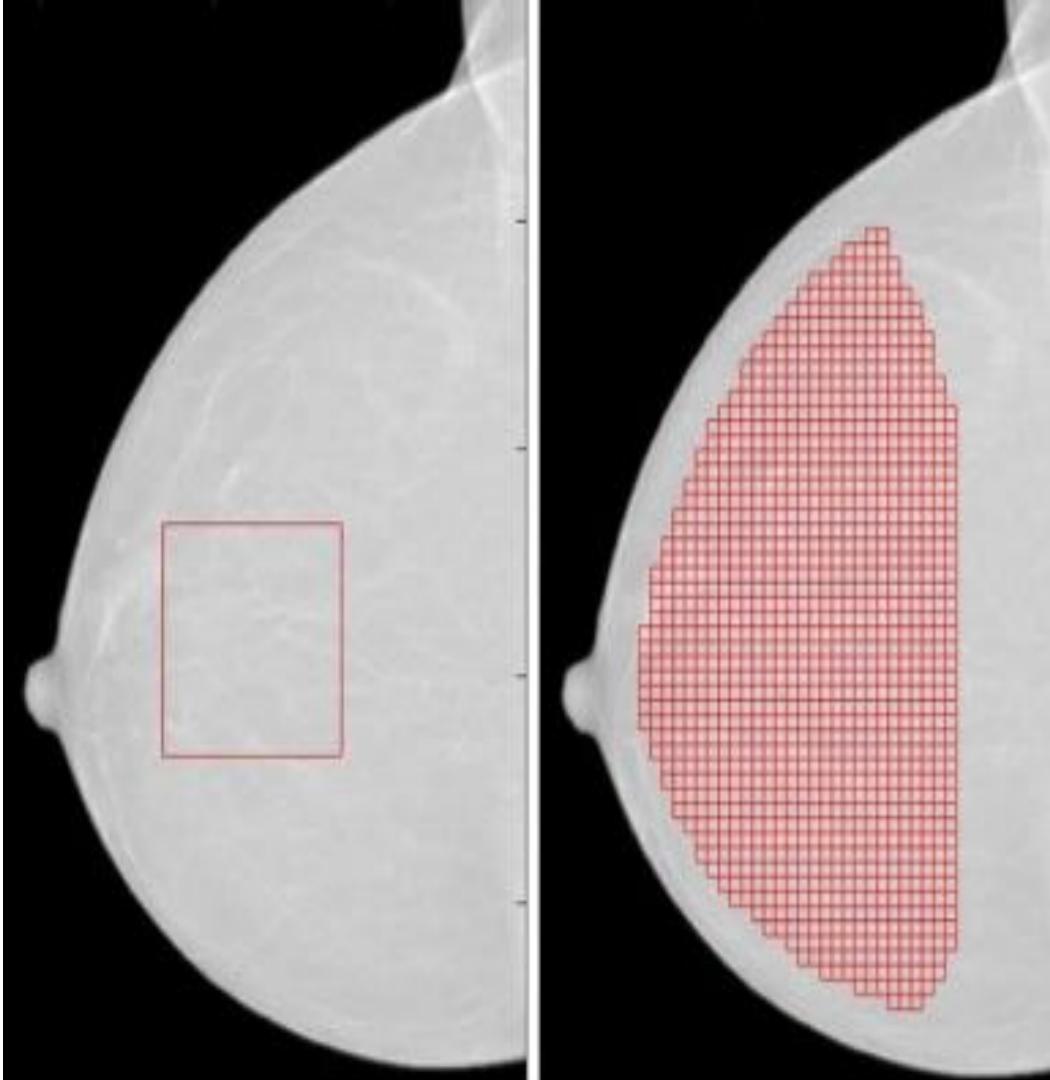
Step 4

False positive
reduction





Radiomics Module





M P R L
Medical Physics Research Laboratory

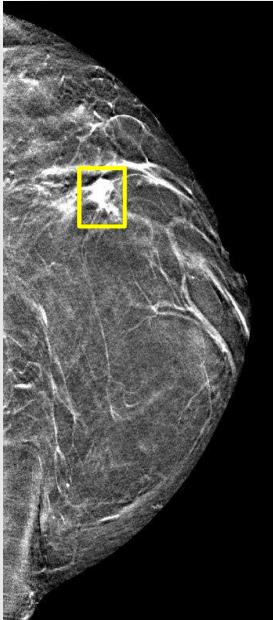
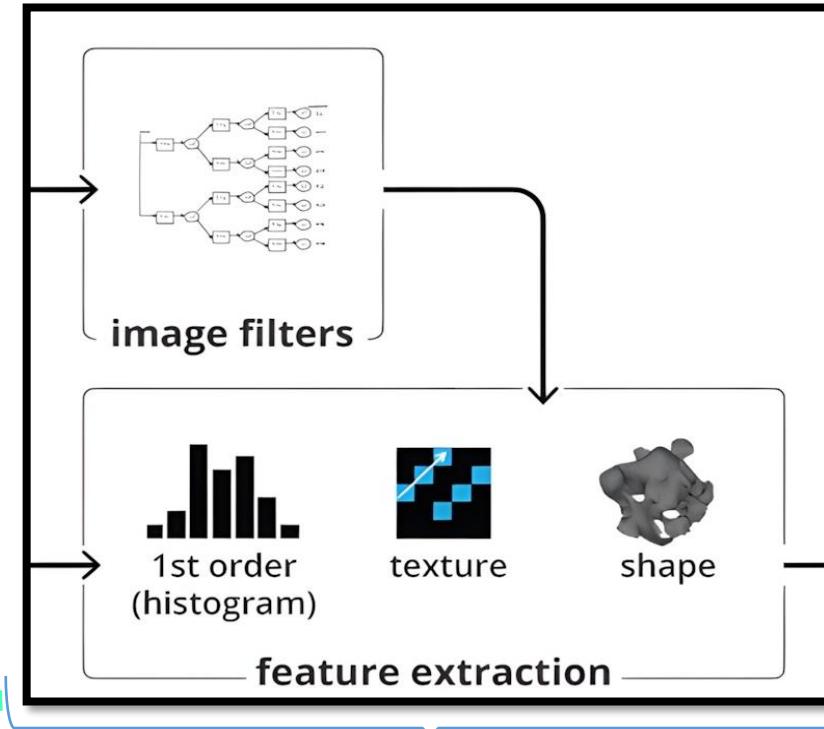
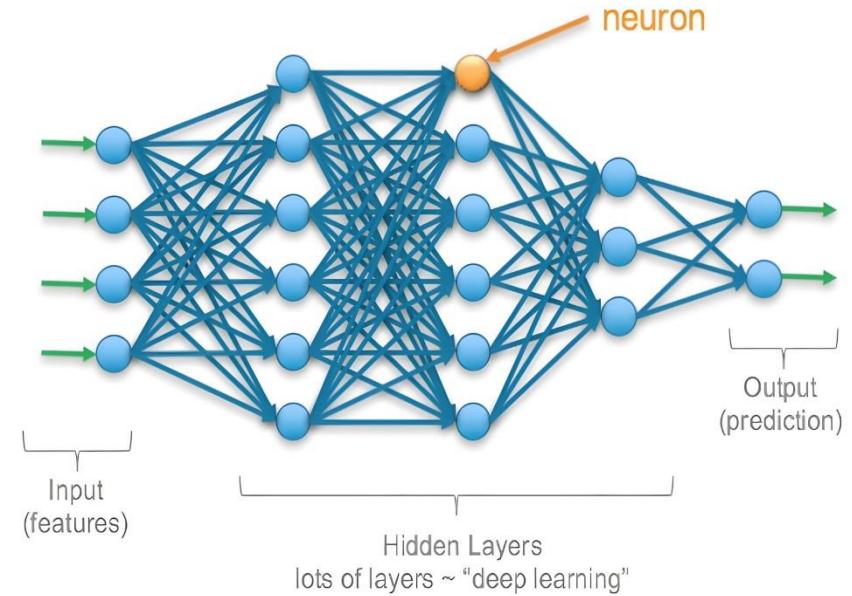
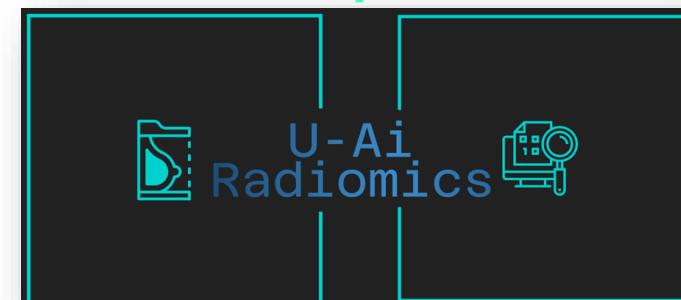


Image Segmentation



PyRadiomics



TabNet

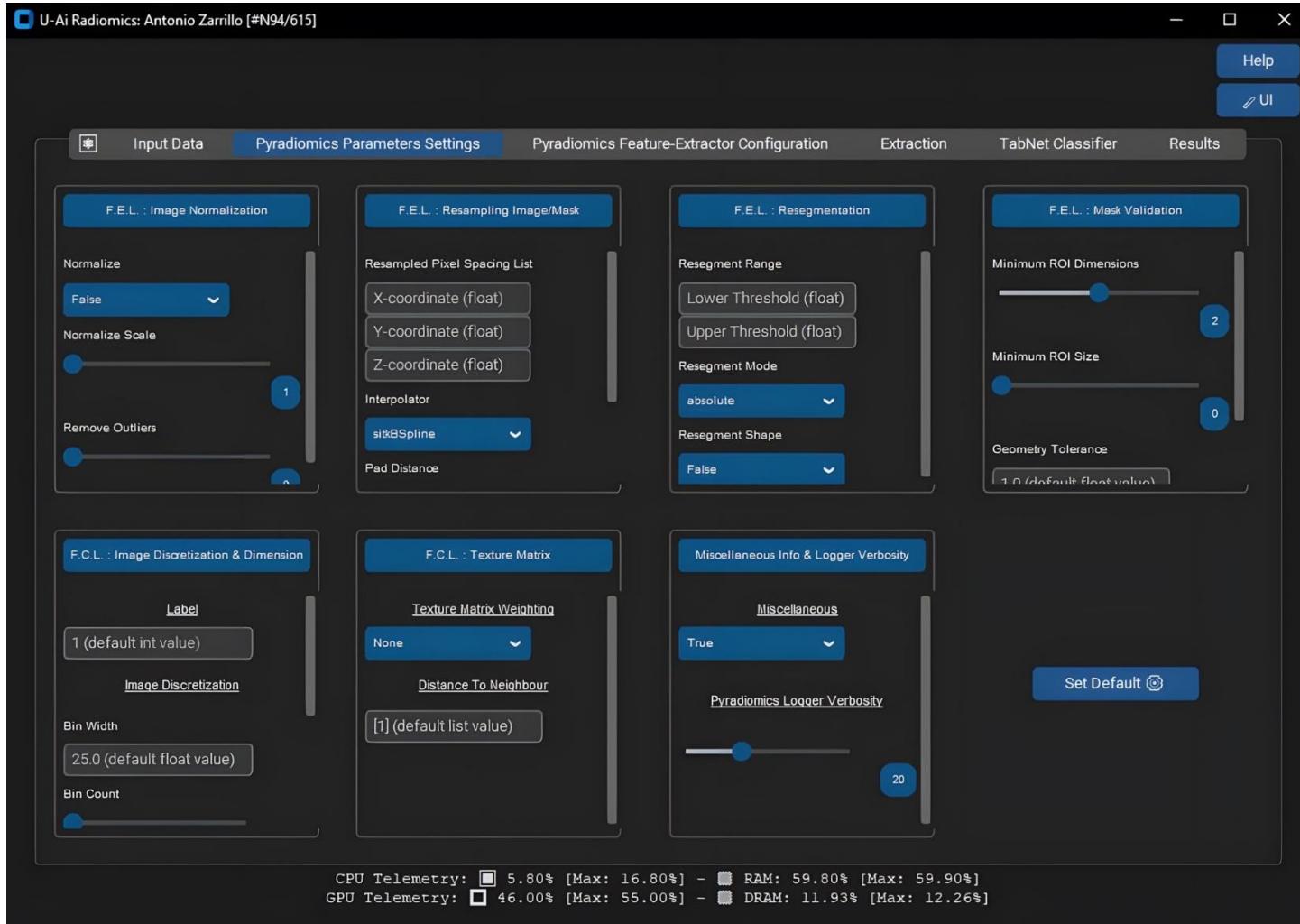


University of Naples "Federico II"- Physics Department "Ettore Pancini"
National Institute of Nuclear Physics

INFN
Istituto Nazionale di Fisica Nucleare



U-Ai Radiomics Parameters Settings Tab



La **PyRadiomics Parameters Settings Tab** consente di configurare i parametri di estrazione di PyRadiomics, distinguendo 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.





U-Ai Radiomics Features Extractor Configuration Tab

U-Ai Radiomics: Antonio Zarrillo [#N94/615]

Input Data Pyradiomics Parameters Settings Pyradiomics Feature-Extractor Configuration Extraction TabNet Classifier Results

First Order Statistics Feature Class

3D Shape-Based Feature Class

2D Shape-Based Feature Class

Gray Level Co-occurrence Matrix

Gray Level Run Length Matrix

Gray Level Size Zone Matrix

Neighbouring Gray Tone Difference Matrix

Gray Level Dependence Matrix

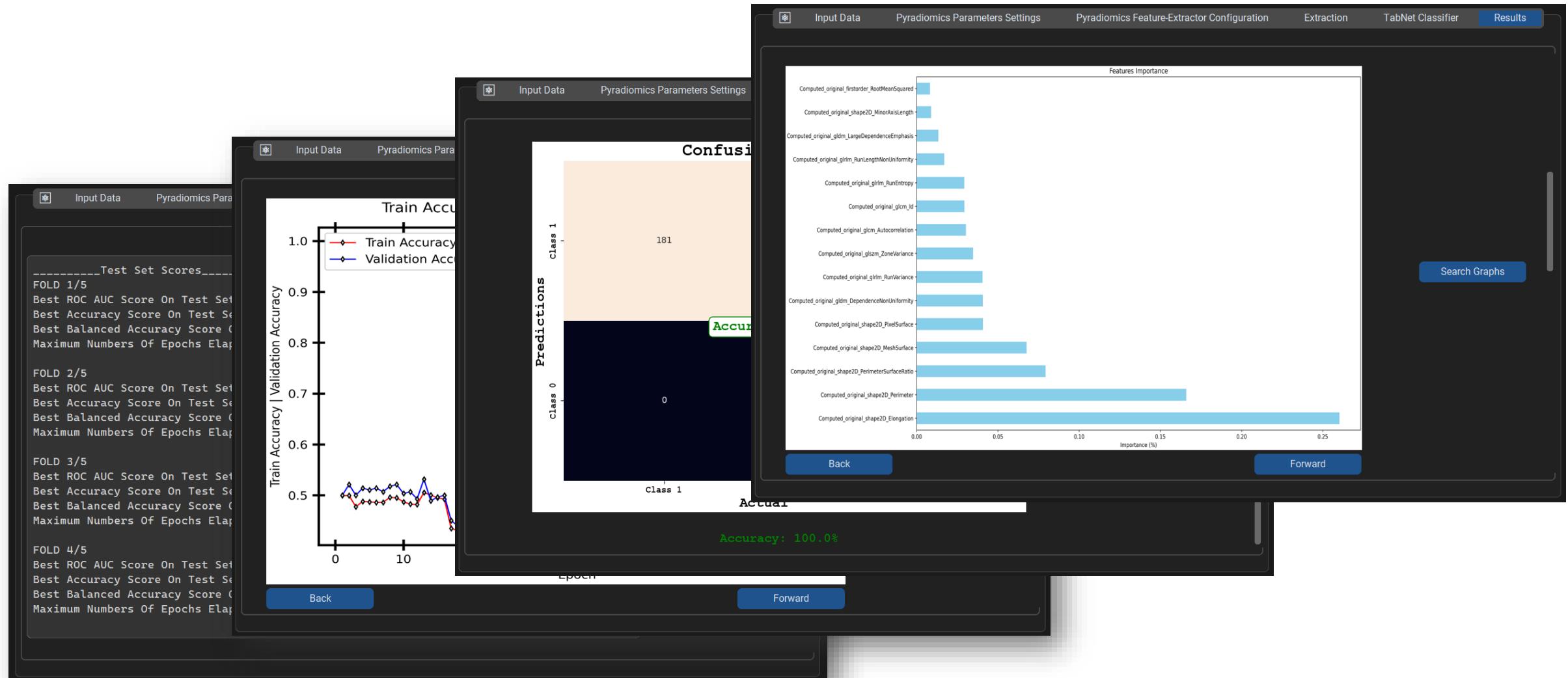
CPU Telemetry: 4.70% [Max: 16.80%] - RAM: 59.70% [Max: 59.90%]
GPU Telemetry: 16.00% [Max: 55.00%] - DRAM: 11.96% [Max: 12.26%]

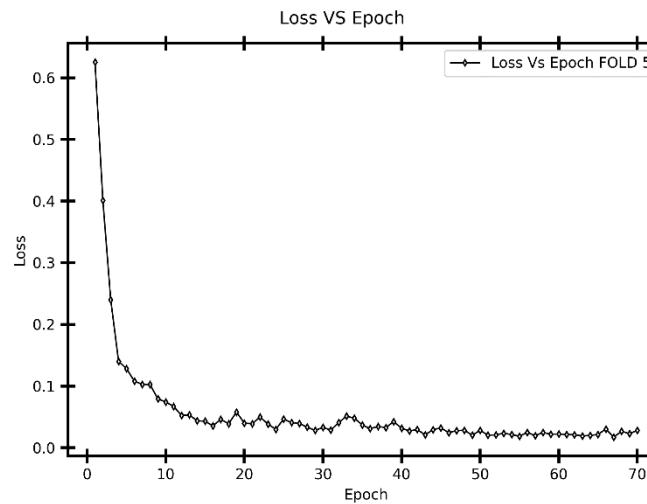
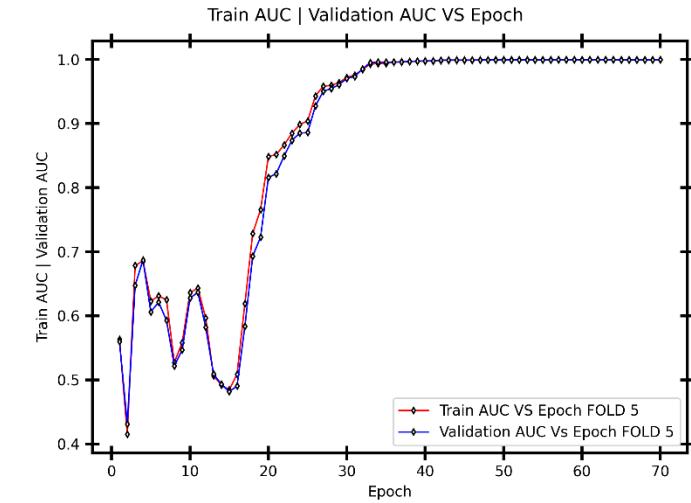
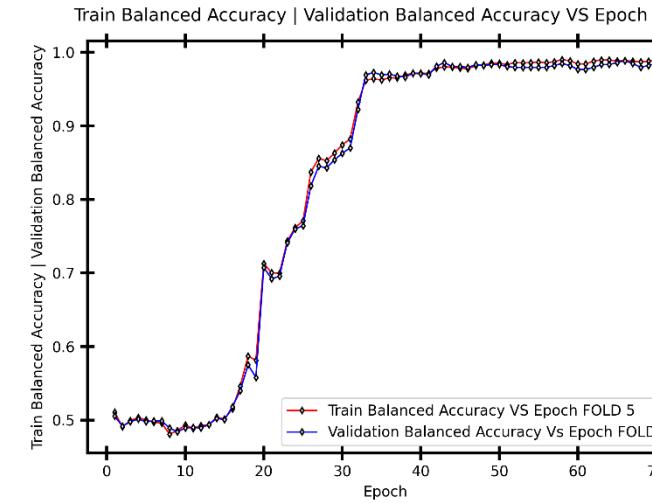
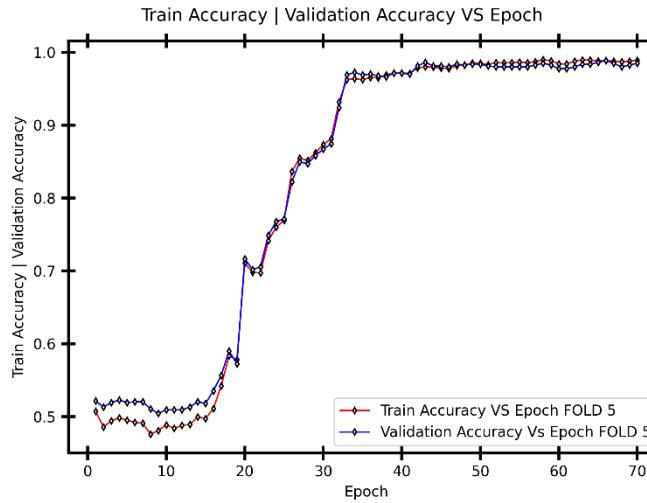
La **PyRadiomics Features Extractor Configuration Tab** consente di selezionare manualmente le features che il modulo ferature-extractor andrà a calcolare entro la maschera di segmentazione:

- **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		
Accuracy	Balanced Accuracy	AUC	Accuracy	Balanced Accuracy	AUC
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_glcm_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_glrlm_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 Nd = 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_glrlm_RunLengthNonUniformity	6.87
Computed_original_firstorder_Energy	5.28
Computed_original_shape2D_PixelSurface	4.92
Computed_original_glcm_Correlation	4.61
Computed_original_glcm_ClusterShade	4.23
Computed_original_glcm_MCC	3.63
Computed_original_firstorder_Skewness	3.60
Computed_original_glcm_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





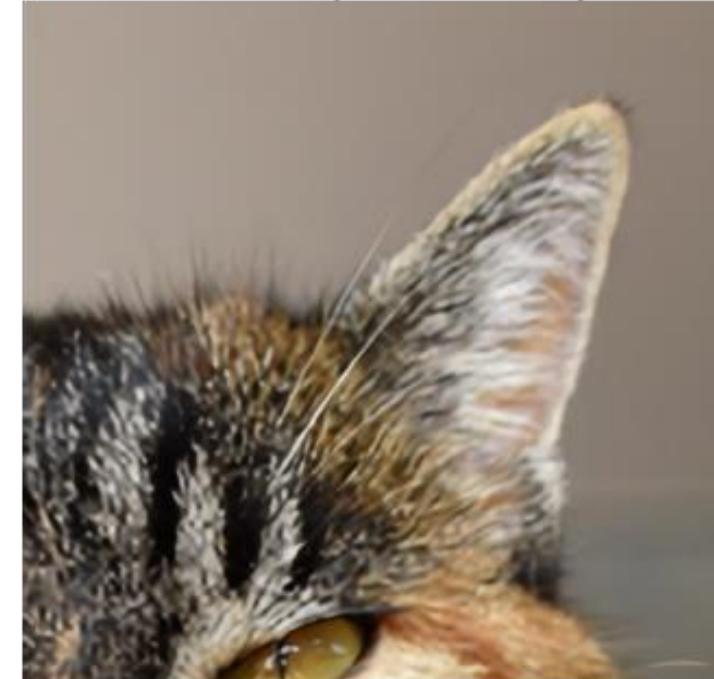
M P R L
Medical Physics Research Laboratory

Super Resolution Neural Network

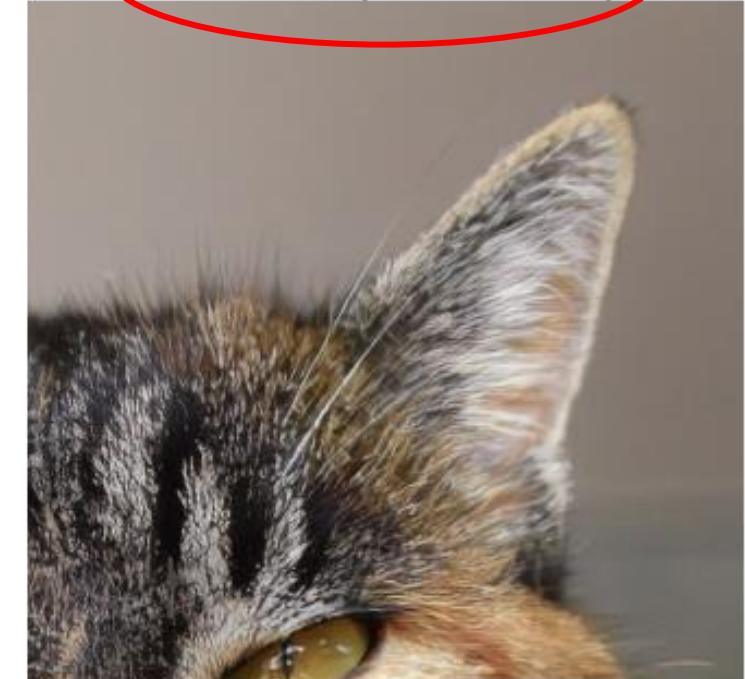
Original (118x124)



EDSR (472x496)



SRGAN (472x496)



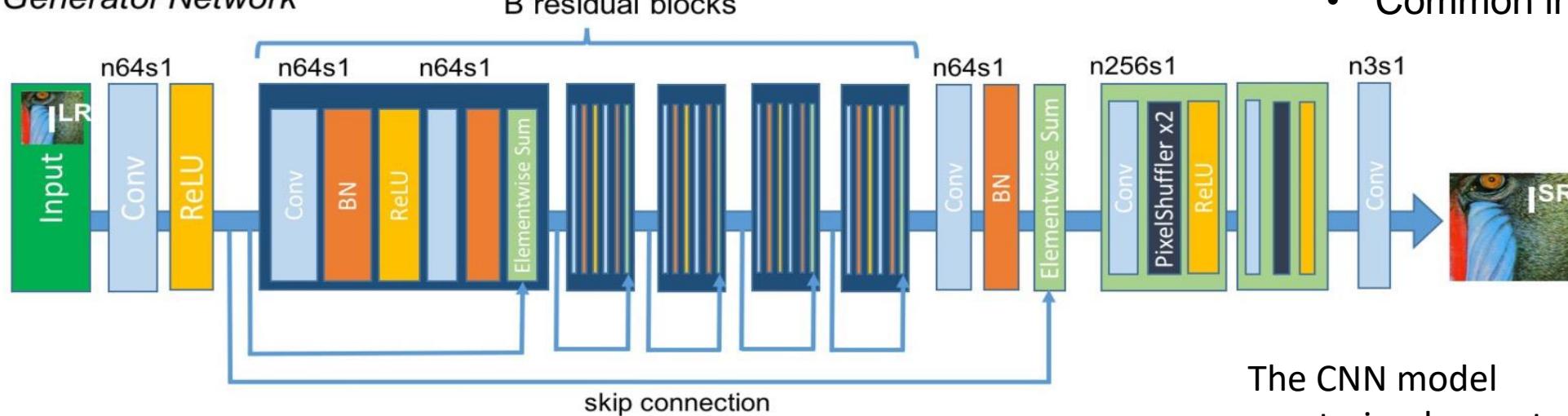
University of Naples "Federico II"- Physics Department "Ettore Pancini"
National Institute of Nuclear Physics

INFN
Istituto Nazionale di Fisica Nucleare



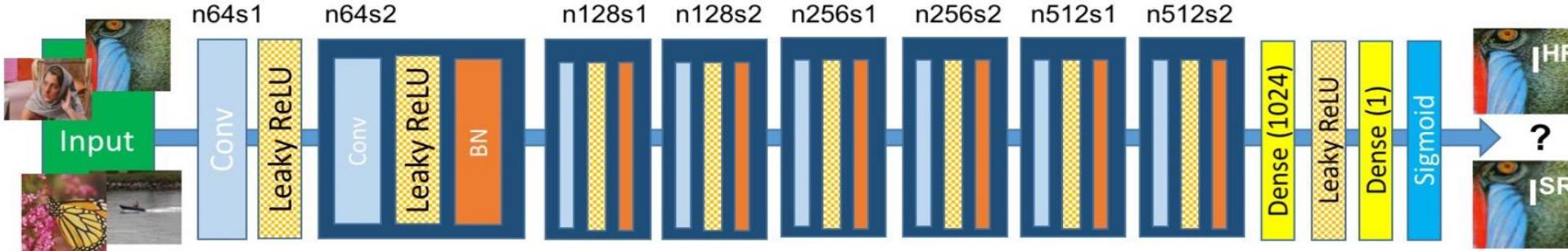
GAN model architecture

Generator Network

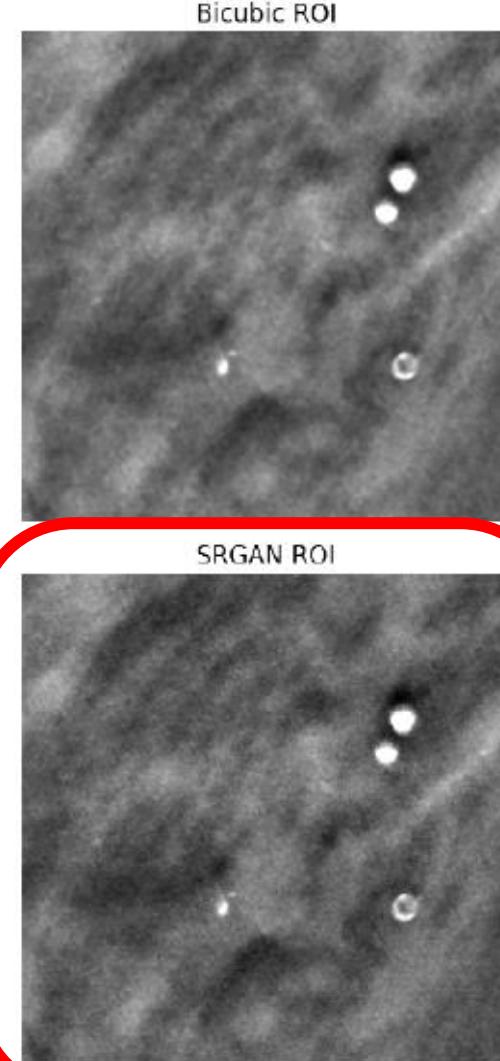
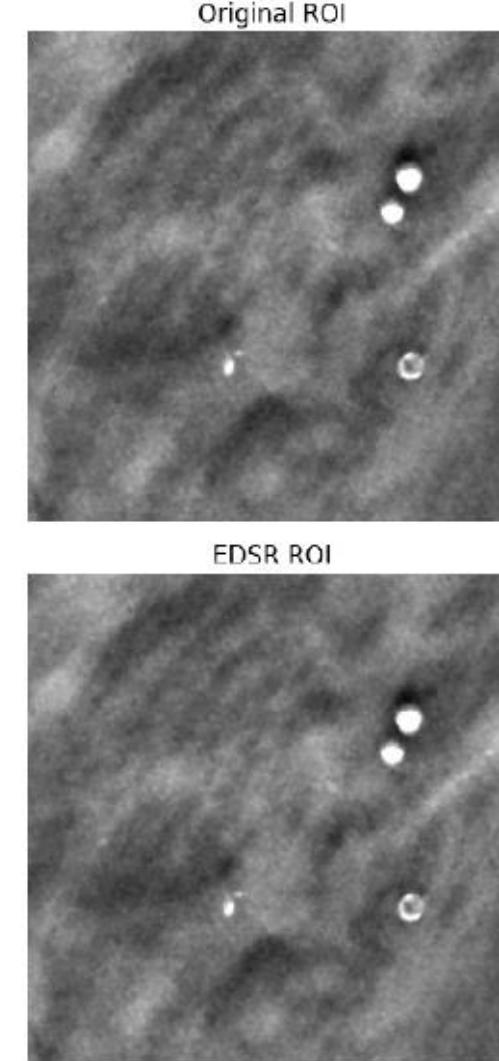
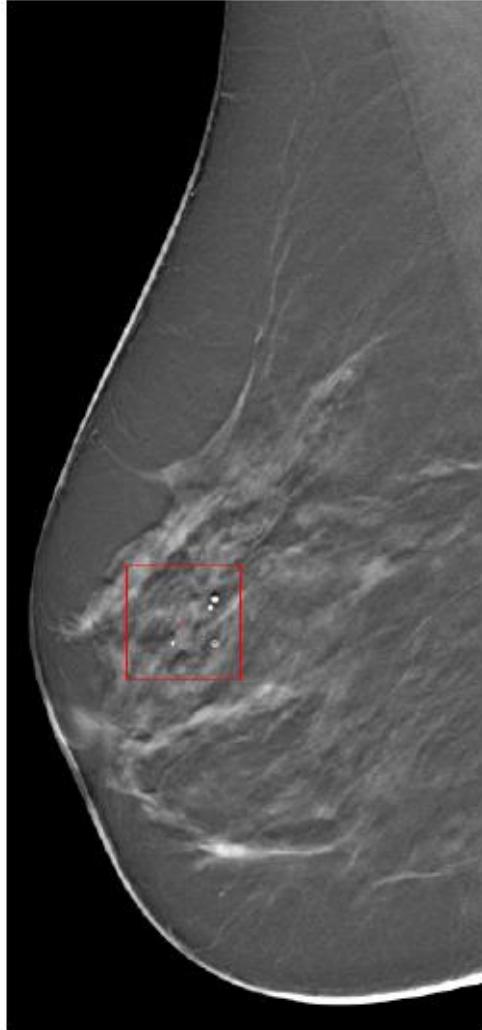


- SRGAN model → 1.55M parameters
- Common input shape → (512×512)

Discriminator Network

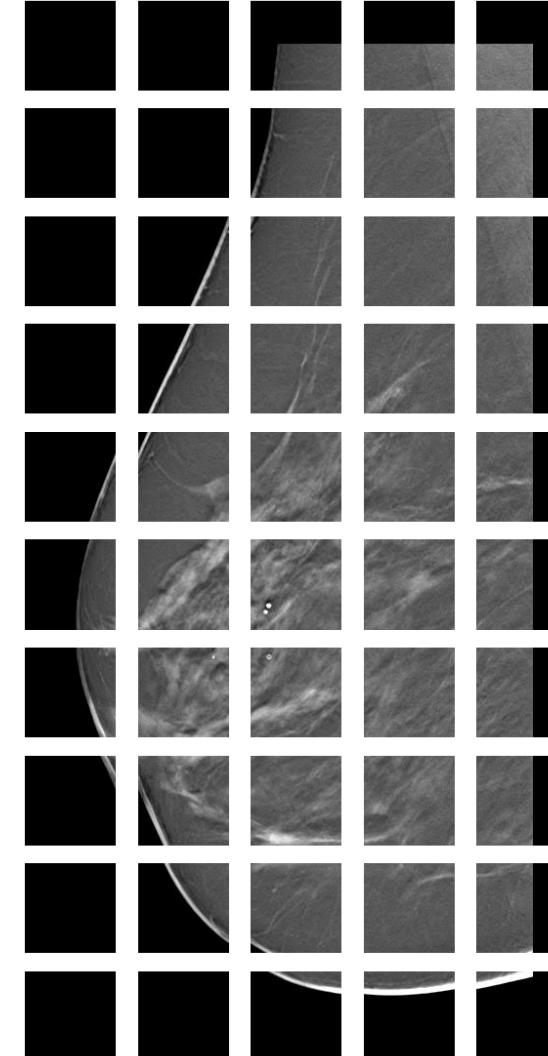


The CNN model
was trained on natural images (DIV2K dataset)





- Current input shape
 $2400 \times 1100 \leftarrow \text{unfeasible}$
- Split image into a series of disjointed patches
(256×256)
- Monitor the boundary effect related to image reconstruction



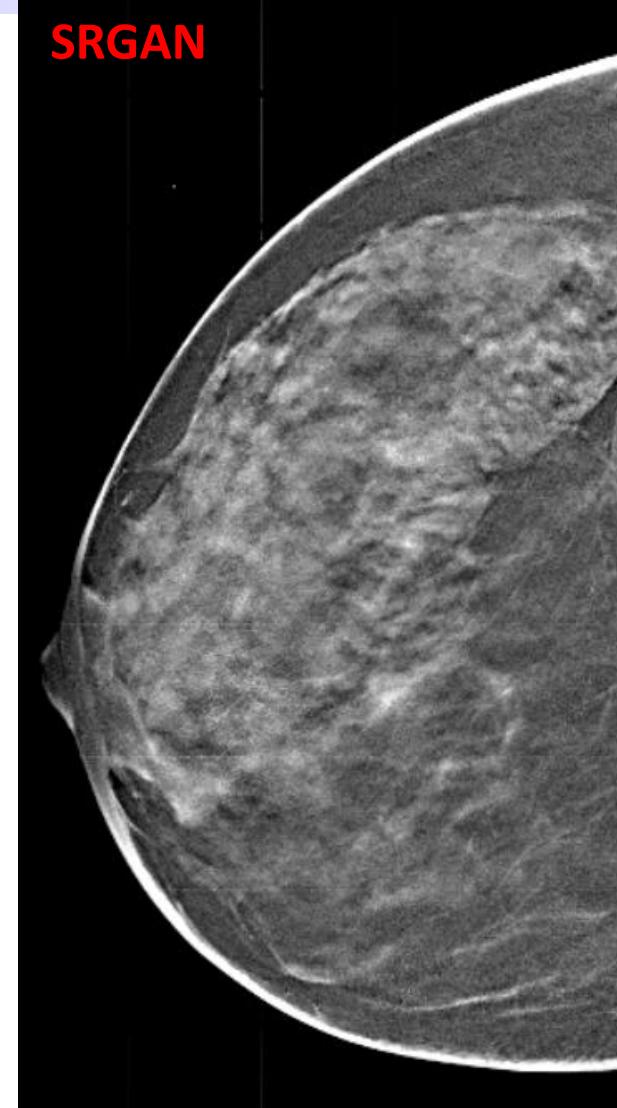
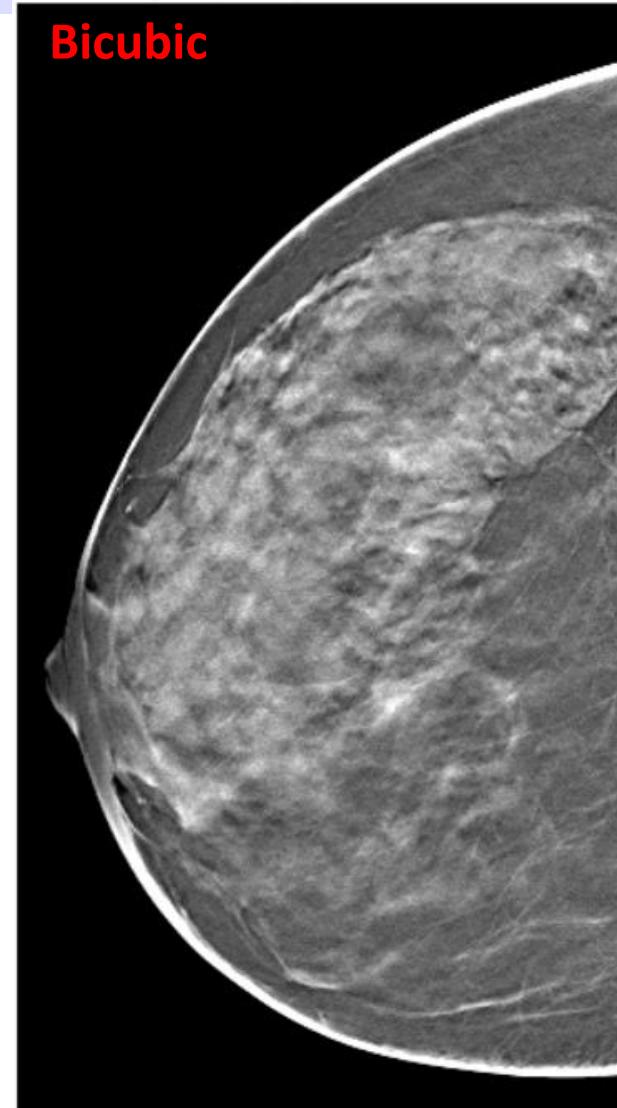
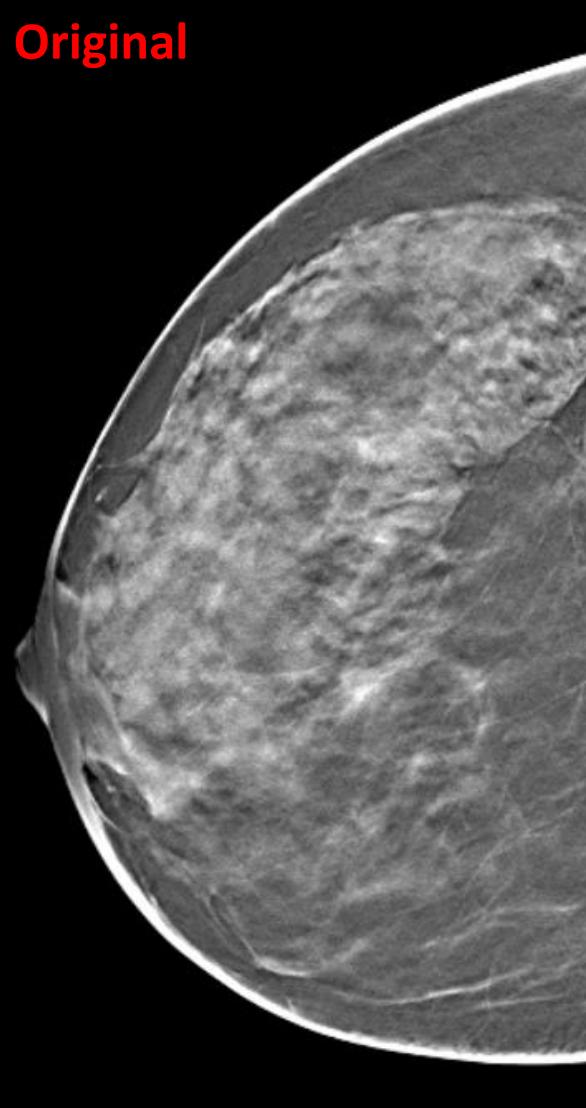
Computational time requires for the SR of the entire image is around 7s





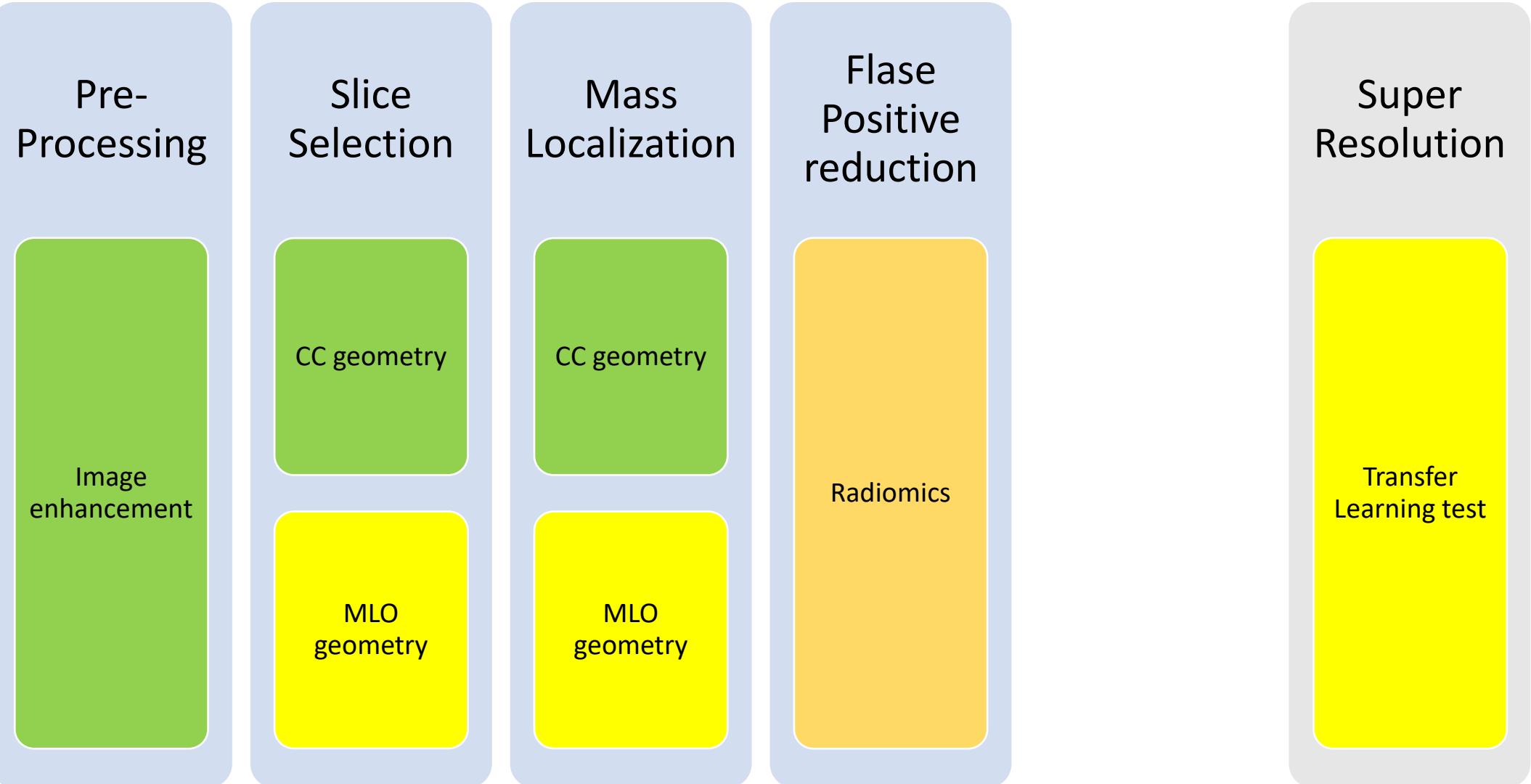
M P R L
Medical Physics Research Laboratory

Examples



University of Naples "Federico II"- Physics Department "Ettore Pancini"
National Institute of Nuclear Physics

INFN
Istituto Nazionale di Fisica Nucleare





Grazie per l'attenzione



Prof. Giovanni Mettivier
Associate Professor of Applied Physics
Medical Physics Specialist
Local Coordinator of INFN Technological Research

