2nd PANHELLENIC CONGRESS OF MEDICAL PHYSICS
4-6 OCTOBER 2024| EUGENIDES FOUNDATION

Setting up an efficient base deep network architecture for medical image segmentation

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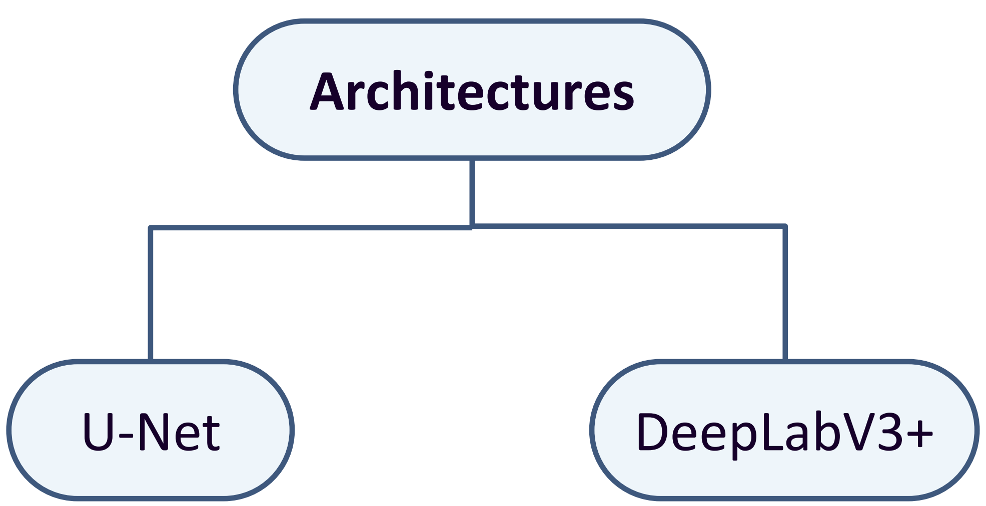
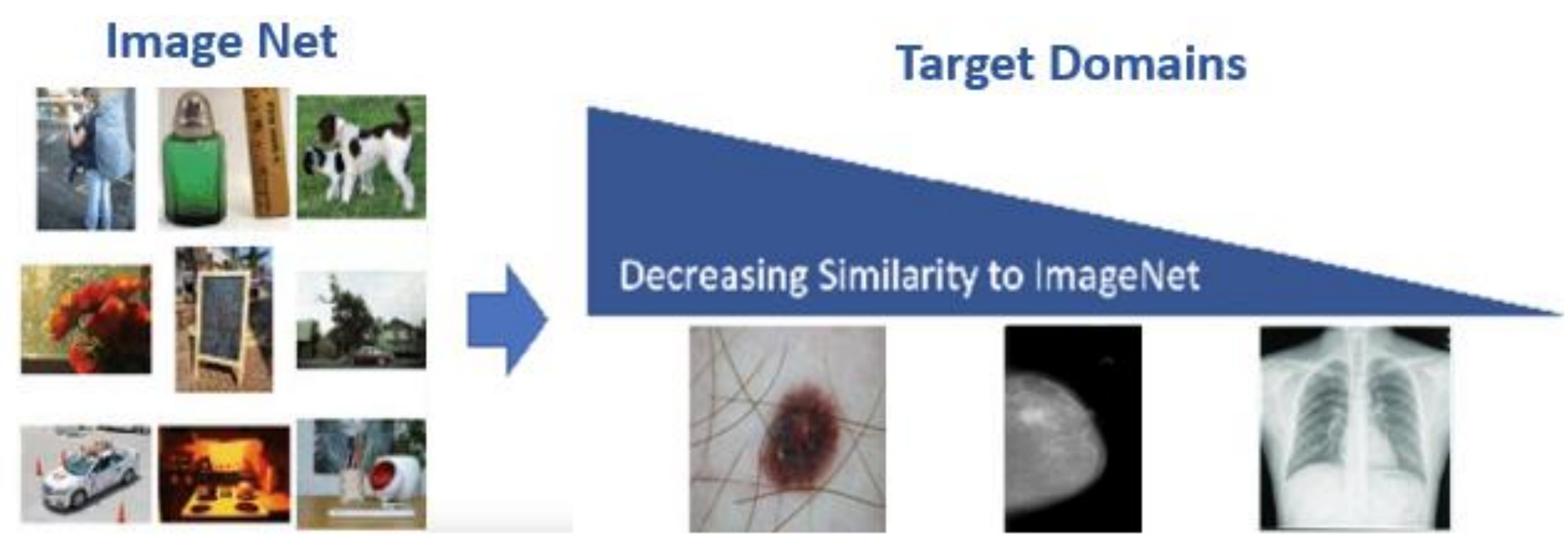
1. Background-Aim

In the realm of deep learning, semantic segmentation is the primary method of identification of regions of interest within medical images. U-Net and DeepLabV3+ are the most popular architectures used in addressing the multifaceted demands of medical image segmentation tasks. However, there is a great number of proposed variants of these architectures, tailored to address specific challenges and optimize performance.

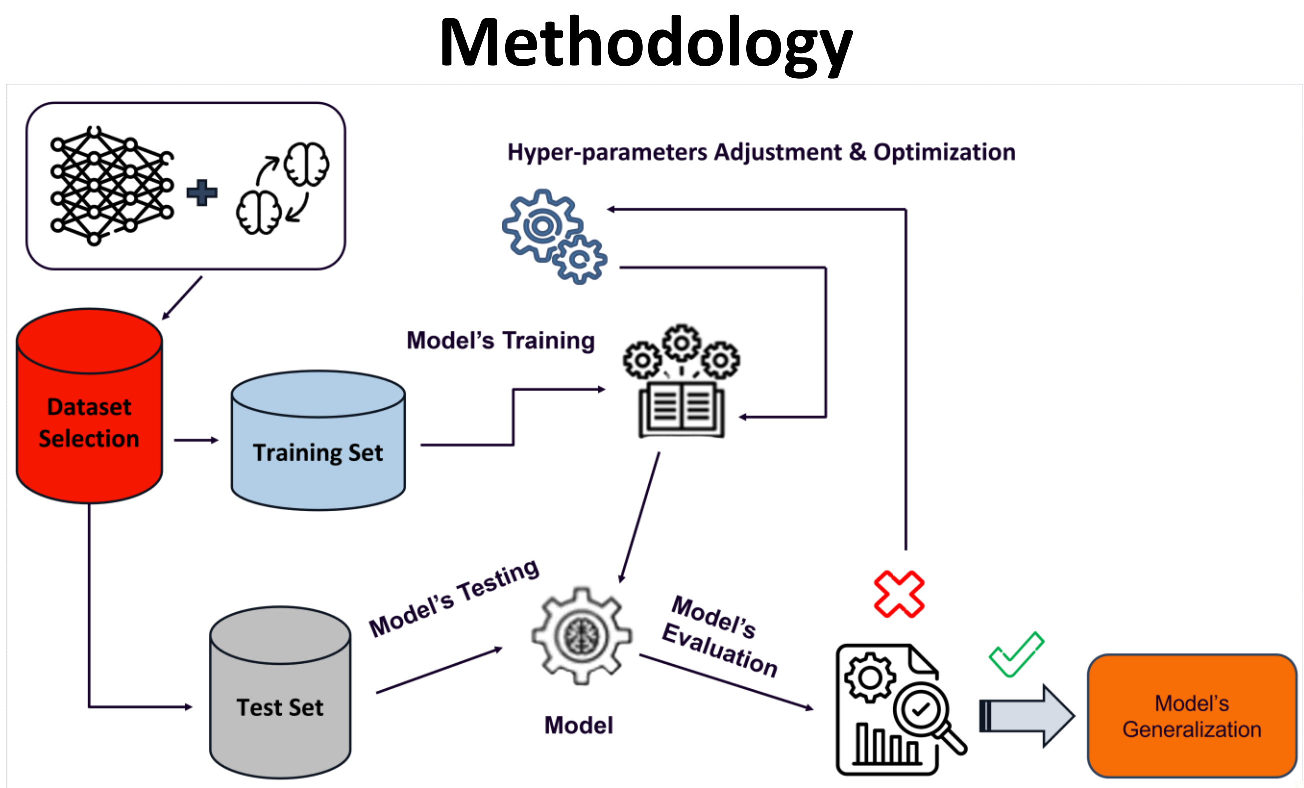
This study aims to evaluate the performance of U-Net and DeepLabV3+ variants in diverse medical segmentation tasks and suggest an efficient and computational effective architecture that could serve as the foundational framework for future research endeavors.

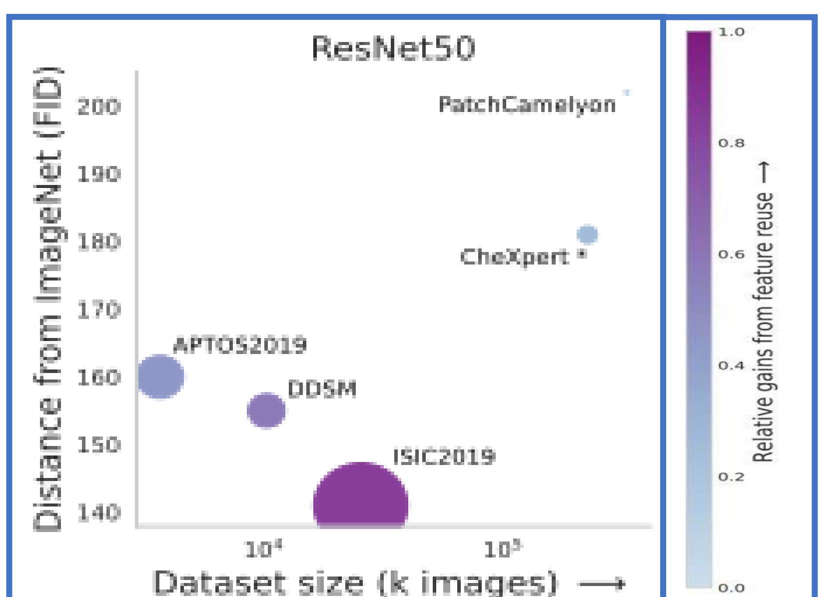
The optimized structure takes advantage of transfer learning and its capabilities, in order to be generalized for different medical image segmentation tasks. In particular, the performance of these deep learning network architectures on three different segmentation tasks of increasing difficulty and graded similarity from ImageNet is examined.

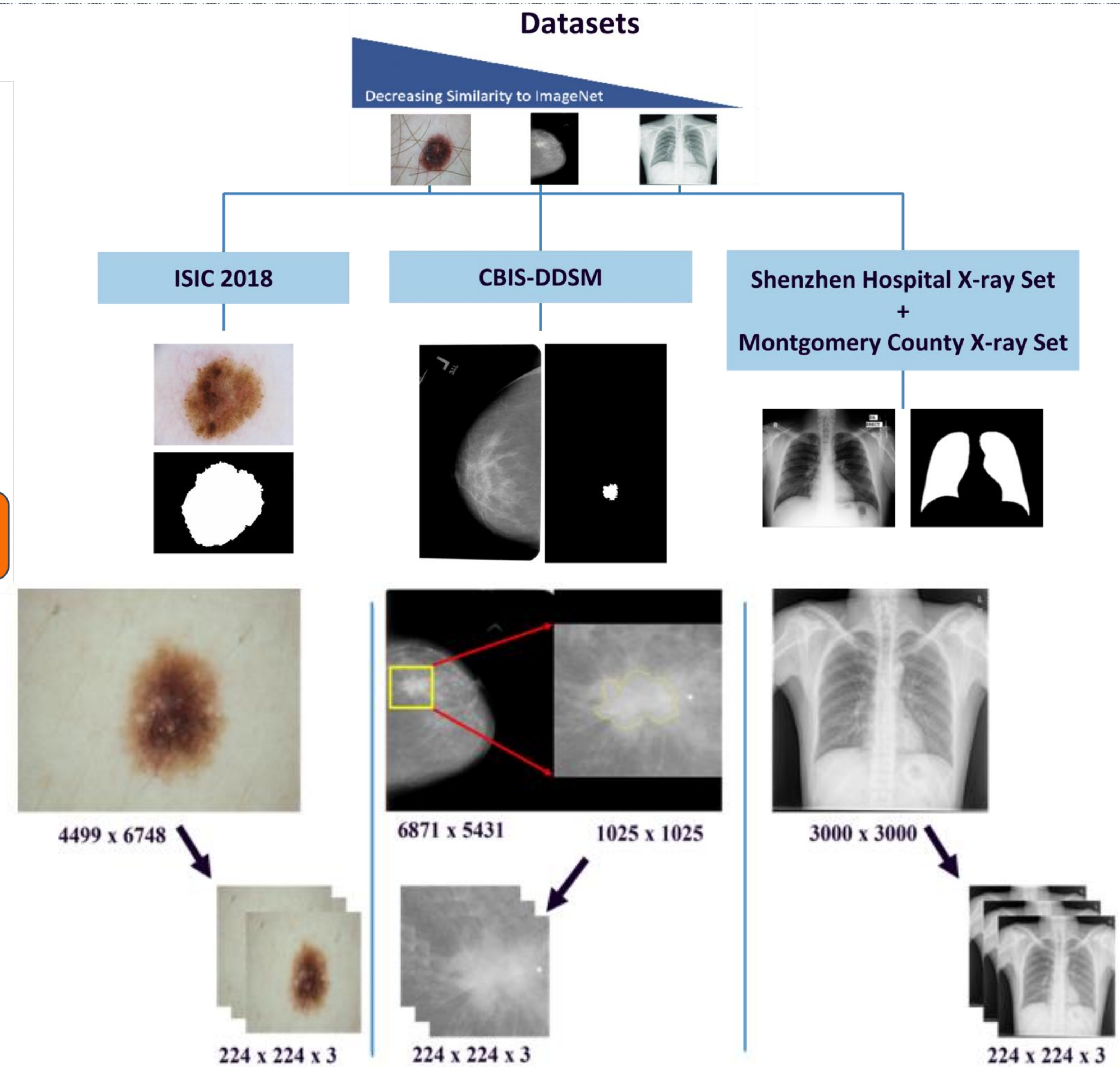




2. Materials & Methods



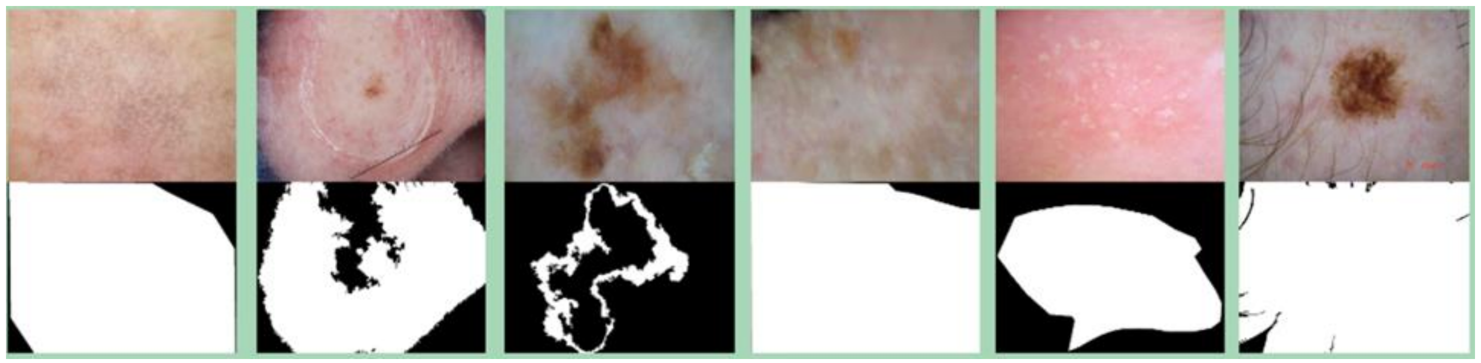




Matsoukas et al. (2022) “What Makes Transfer Learning Work For Medical Images: Feature Reuse & Other Factors”

2. Materials & Methods

Data Quality Inspection



	ISIC 2018	
	Training	Test
Starting Data	2594	1000

	ISIC 2018	
	Training	Test
Final Data	2480	1000

	Shenzhen Hospital CXR Set	Montgomery CXR Set
	Training	Test
Final Data	566	138

	Masses in CBIS-DDSM	
	Training	Test
Final Data	1301	377

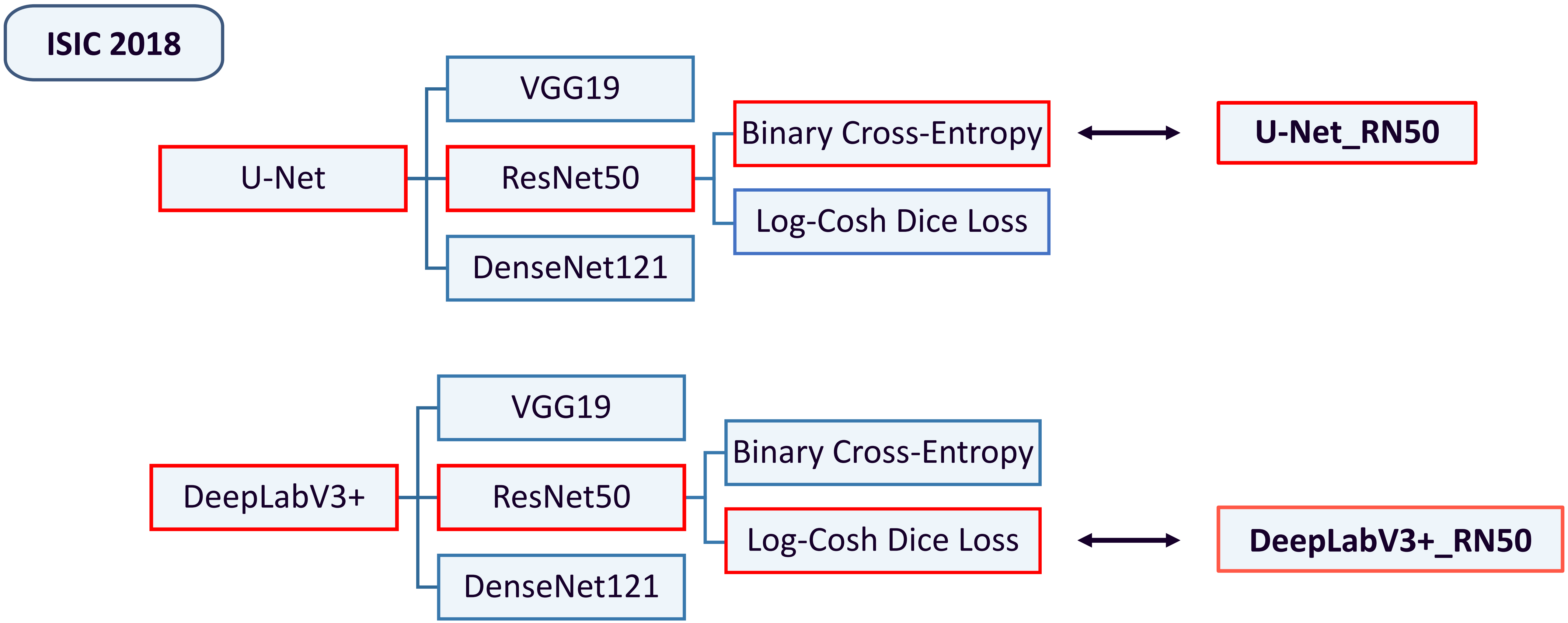
Hyper-parameters

ADAM (Adaptive Moment Estimation)	
Learning Rate	Lr = 0.001
Batch Size	Batch Size = 32
Epochs	Epochs = 50
Early Stopping	Early Stopping = True, min_delta = 0.001, patience = 5

Loss Functions

Binary Cross-Entropy
Log-Cosh Dice Loss

3. Results



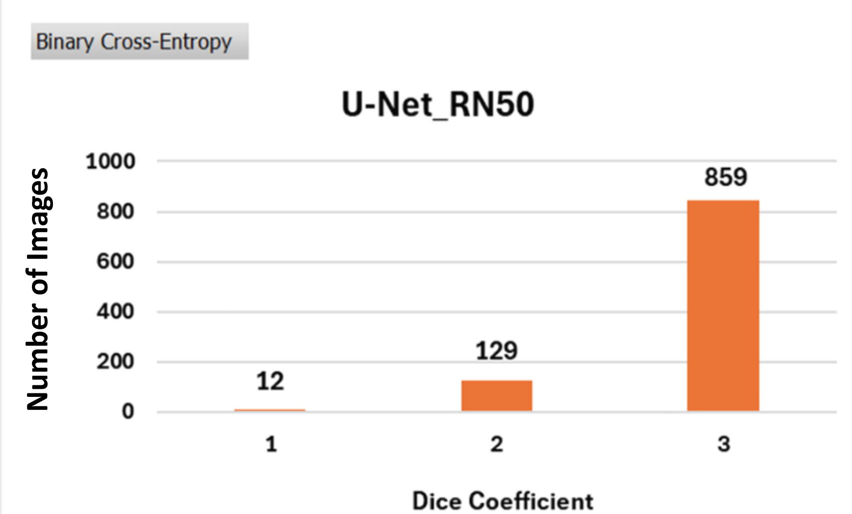
Dice Coeffient			
	224 x 224 - Binary Cross-Entropy		
	VGG19	ResNet50	DenseNet121
U-Net	0.717	**0.878**	0.848
DeepLabV3+	0. 815	**0.860**	0.853

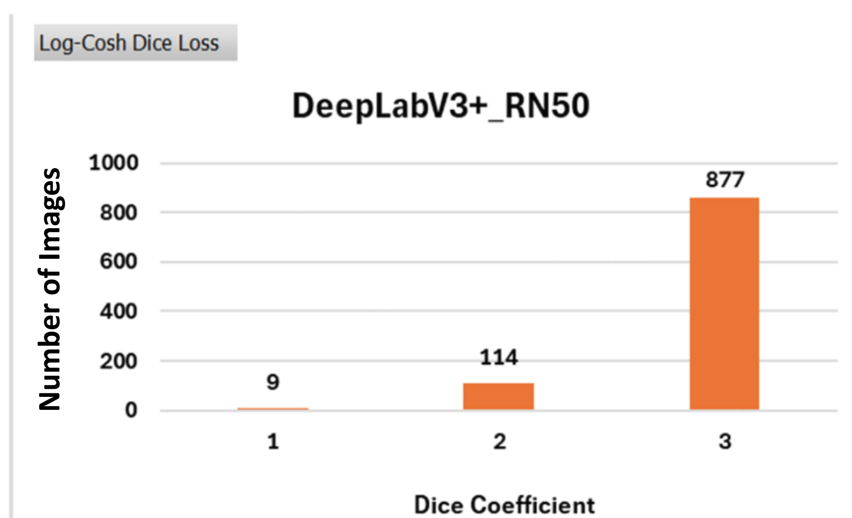
Dice Coefficient		
	Loss Functions	
	Binary Cross-Entropy	Log-Cosh Dice Loss
DeepLabV3+_RN50	0.860	**0.893**
U-Net_RN50	0.878	0.854

3. Results

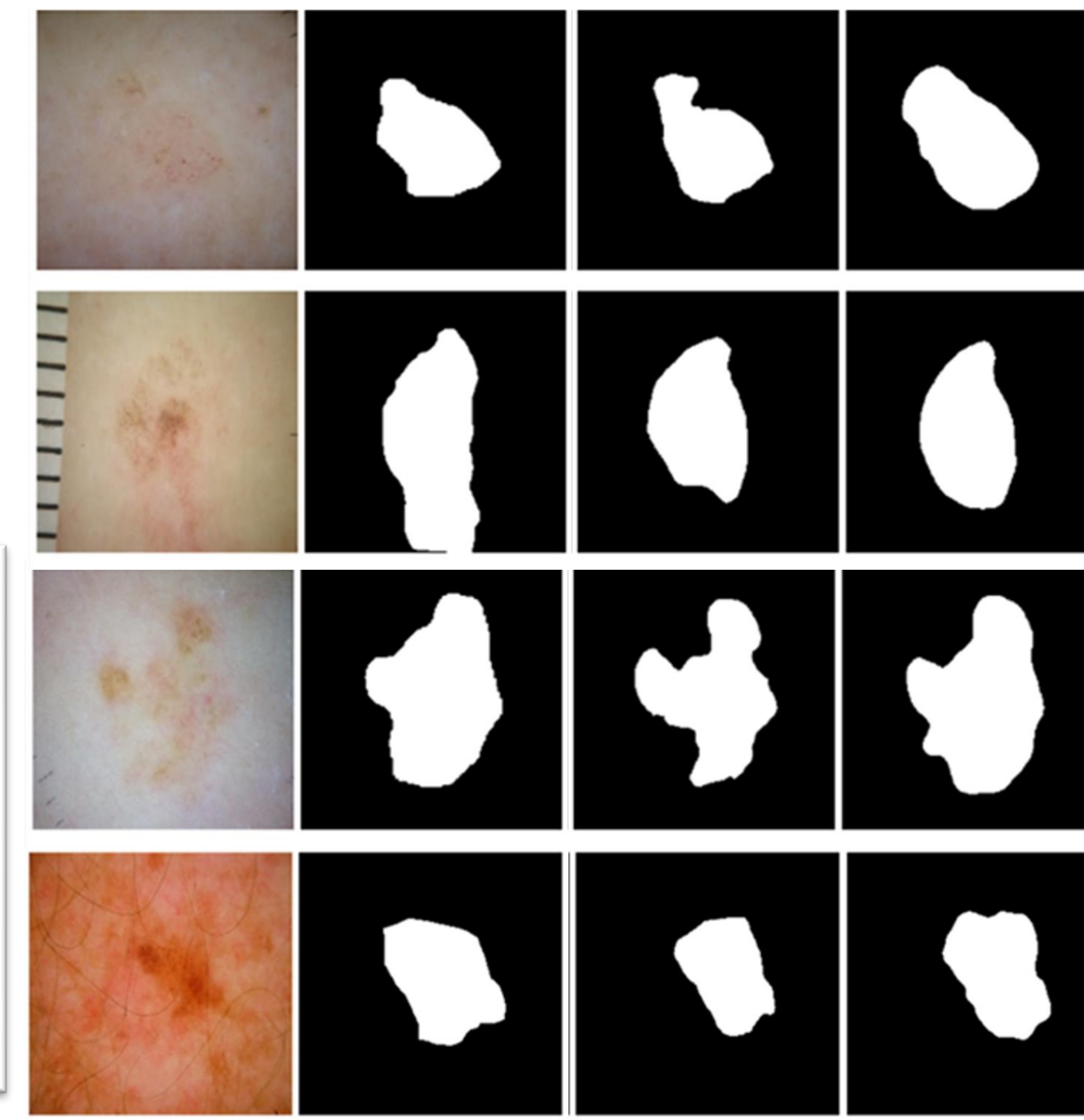
ISIC 2018

ISIC 2018		
	Dice Coefficient	
Image	**U-Net_RN50**	**DeepLabV3+_RN50**
ISIC_0021036.jpg	0.723	0.809
ISIC_0021583.jpg	0.618	0.734
ISIC_0022736.jpg	0.584	0.873
ISIC_0036235.jpg	0.806	0.827





Original Image	Ground Truth Mask	U-Net_RN50	DeepLabV3+_RN50



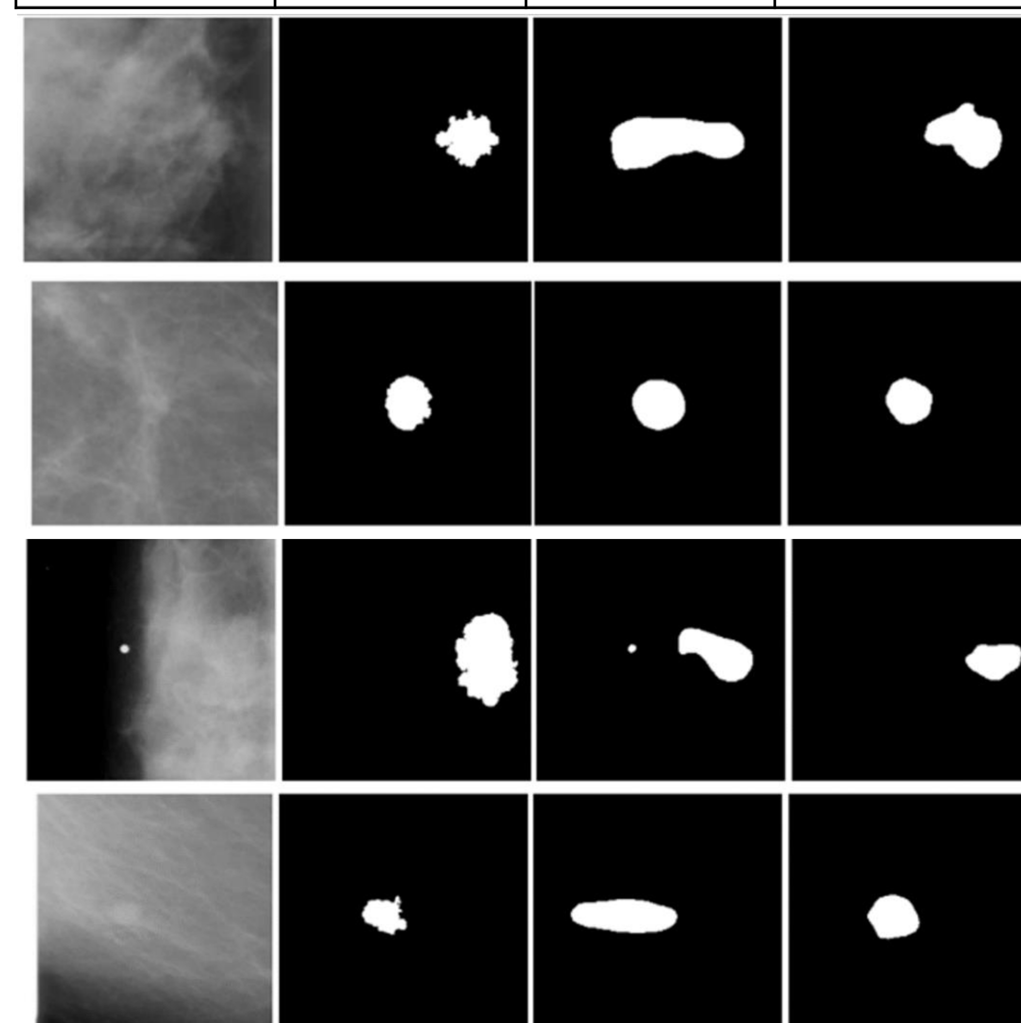
3. Results

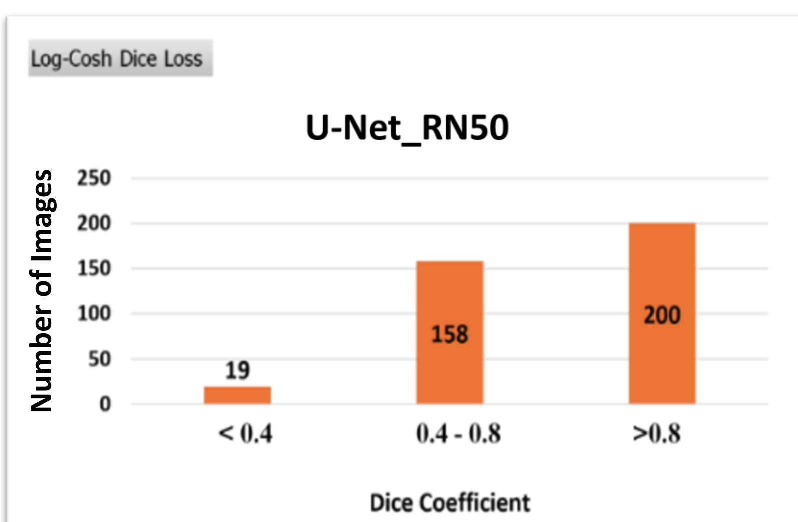
Masses in CBIS-DDSM

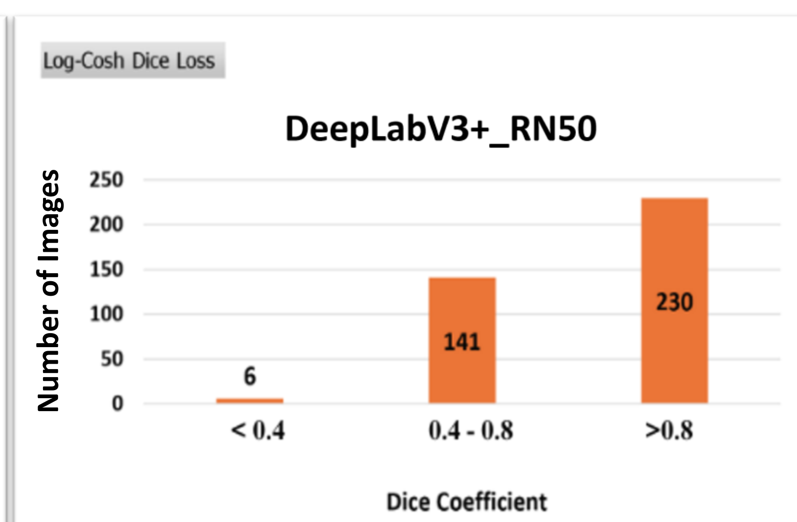
Masses in CBIS - DDSM				
	224 x 224 – Binary Cross-Entropy		224 x 224 - Log-Cosh Dice Loss	
	U-Net_RN50	DeepLabV3+_RN50	U-Net_RN50	DeepLabV3+_RN50
Dice Coefficient	0.748	0.750	0.756	**0.789**

Masses in CBIS-DDSM		
	Dice Coefficient	
Image	U-Net_RN50	DeepLabV3+_RN50
Mass-Test_P_00066_LEFT_CC_1.jpg	0.533	0.855
Mass-Test_P_00875_RIGHT_CC_1.jpg	0.766	0.841
Mass-Test_P_01719_RIGHT_MLO_1.jpg	0.199	0.659
Mass-Test_P_00813_RIGHT_MLO_1.jpg	0.450	0.856

Original Image	Ground Truth Mask	U-Net_RN50	DeepLabV3+_RN50





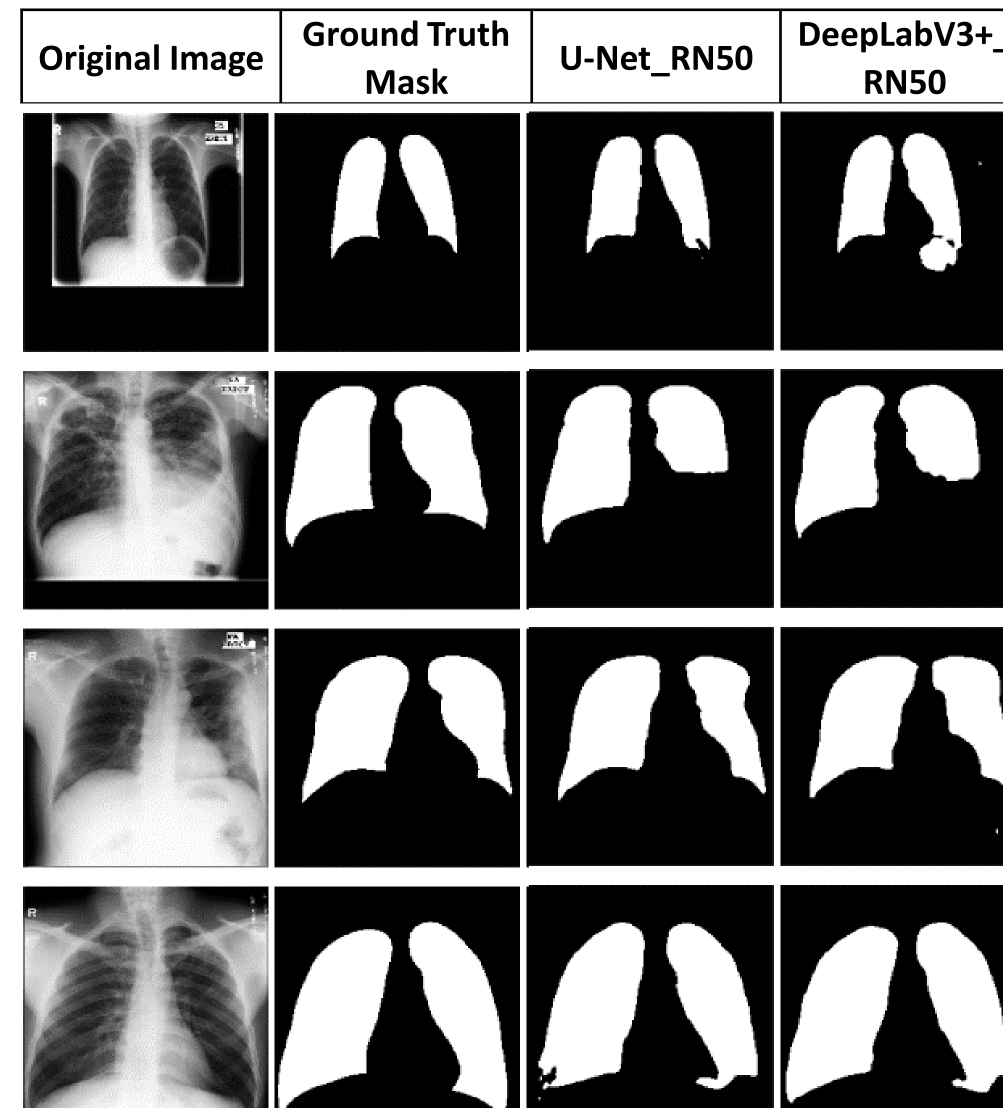


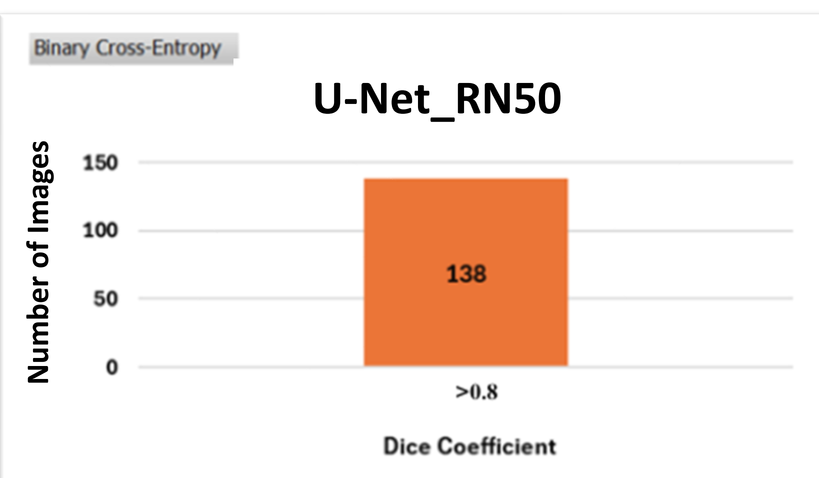
3. Results

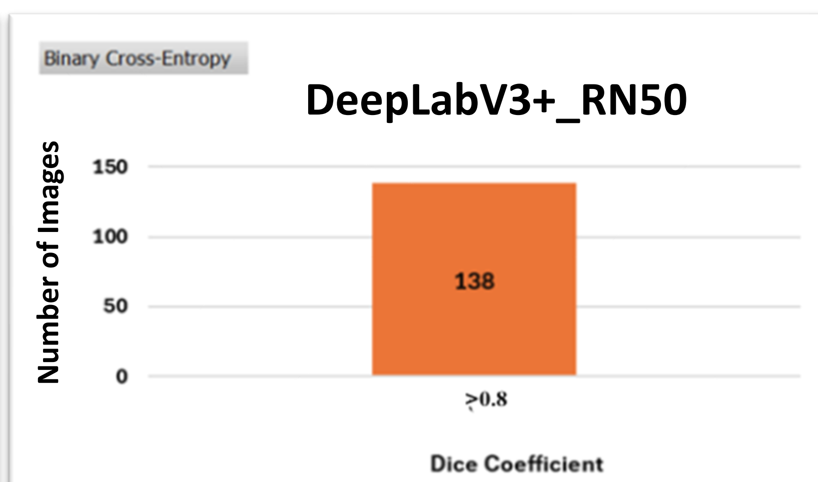
Chest X-rays

	Montgomery County X-ray Set			
	224 x 224 - Binary Cross-Entropy		224 x 224 - Log-Cosh Dice Loss	
	U-Net_RN50	DeepLabV3+_RN50	U-Net_RN50	DeepLabV3+_RN50
Dice Coefficient	0.9540	**0.9544**	0.905	0.951

Montgomery County X-ray Set		
	Dice Coefficient	
Image	U-Net_RN50	DeepLabV3+_RN50
MCUCXR_0077_0.png	0.945	0.901
MCUCXR_0150_1.png	0.877	0.903
MCUCXR_0266_1.png	0.947	0.955
MCUCXR_0338_1.png	0.926	0.954



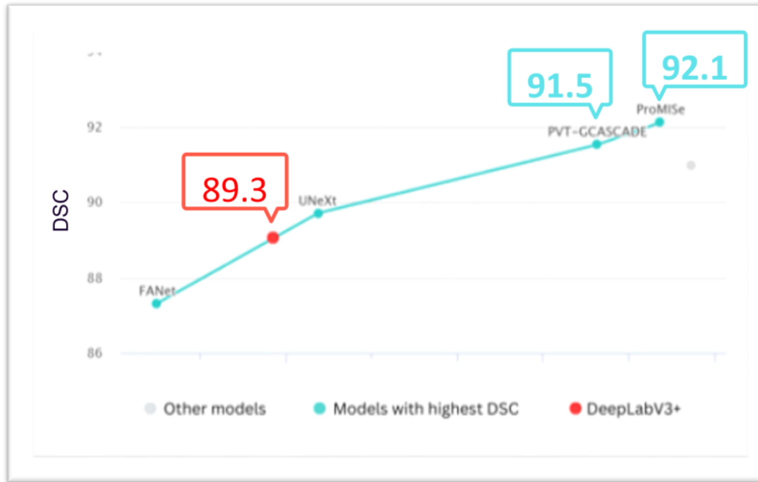


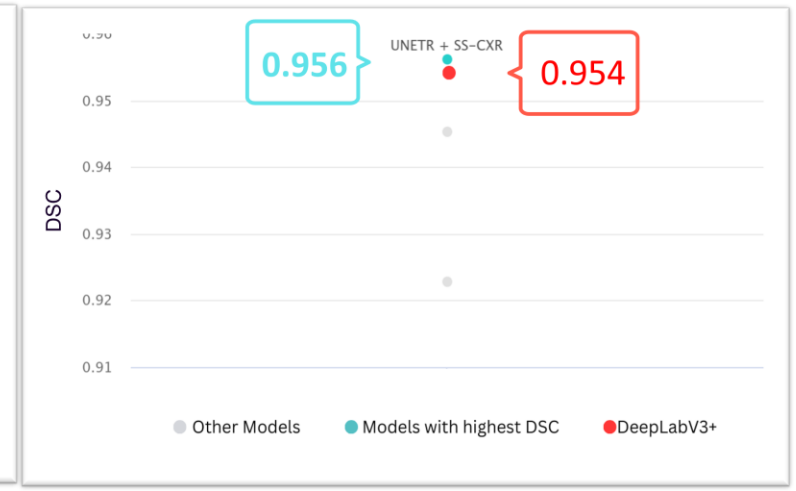


3. Results

The success of the model

Kaggle-based Results



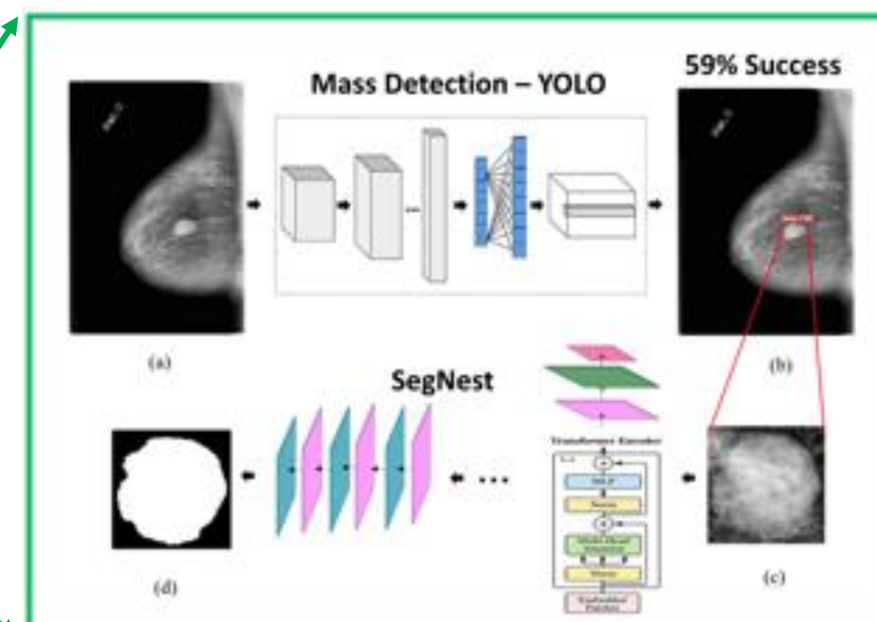


Medical Image Segmentation on ISIC 2018

Semantic Segmentation on Montgomery CXR Set

Paper-based Results

Εργασία	Μοντέλο	Loss Function	Dice Coefficient
Sharif Amit Kamran et al.	Swin-SFTNet	L_{BCE}	24.13%
Bouzar-Benlabiod et al.	U-Net SE-RestNet-101	L_{BCE}	75%
Yuehang Wang et al.	AM-MSP-cGAN	L_{BCE}	84.49%
Dongdong Liu et al.	TrEnD	L_{BCE}	89.48%
Touazi et al.	SegNest	$L_{comb}^{Focal}\ (dice_{weights} = 0.5, focal_{weights} = 0.5)$	90.15%
Our Approach	**DeepLabV3+**	$L_{Log-Cosh\ Dice}$	**78.9%**



Touazi et al. (2023) "Two-Stage Approach for Semantic Image Segmentation of Breast Cancer : Deep Learning and Mass Detection in Mammographic mages"

4. Conclusions

- ❖ The development of user-oriented and computationally efficient models makes semantic segmentation accessible and practical, offering advanced image analysis capabilities in a great number of clinical tasks

- ❖ The DeepLabV3+ architecture using transfer learning of pre-trained neural network, ResNet50, exhibited exceptional results in three different medical image segmentation tasks of graded similarity from ImageNet, setting it up as a fundamental baseline framework in future studies

- ❖ The choice of the appropriate loss function significantly affects the model training and is adapted to the needs of the problem at hand

- ❖ The quality of the data is crucial to further improve the performance of the model. Hence, in medical domain it is preferable to implement data-driven rather than model-driven improvements