Deep Learning Analysis in Dermoscopy Images

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Outline

- Motivation
- Image Segmentation Architectures
- Methodology
- Results
- Discussions and Future Works
- Conclusion

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- Background of the Problem
- Aim and Scope
- Challenges
- Why Deep Learning now?

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- Background of the Problem
  - Skin cancer: 100.000+ estimated new case 2020

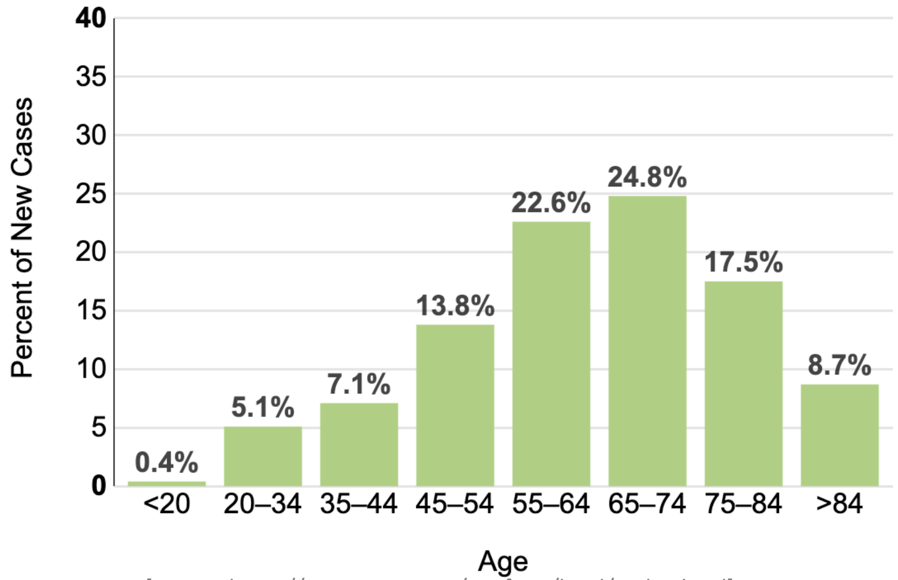
	Common Types of Cancer	Estimated New Cases 2020	Estimated Deaths 2020
1.	Breast Cancer (Female)	276,480	42,170
2.	Lung and Bronchus Cancer	228,820	135,720
3.	Prostate Cancer	191,930	33,330
4.	Colorectal Cancer	147,950	53,200
5.	**Melanoma of the Skin**	**100,350**	**6,850**
6.	Bladder Cancer	81,400	17,980
7.	Non-Hodgkin Lymphoma	77,240	19,940
8.	Kidney and Renal Pelvis Cancer	73,750	14,830
9.	Uterine Cancer	65,620	12,590
10.	Leukemia	60,530	23,100

Melanoma of the skin represents 5.6% of all new cancer cases in the U.S.

[source: https://seer.cancer.gov/statfacts/html/melan.html]

Motivation

- Background of the Problem
  - Skin cancer: 100.000+ estimated new case 2020
  - Early detection matters



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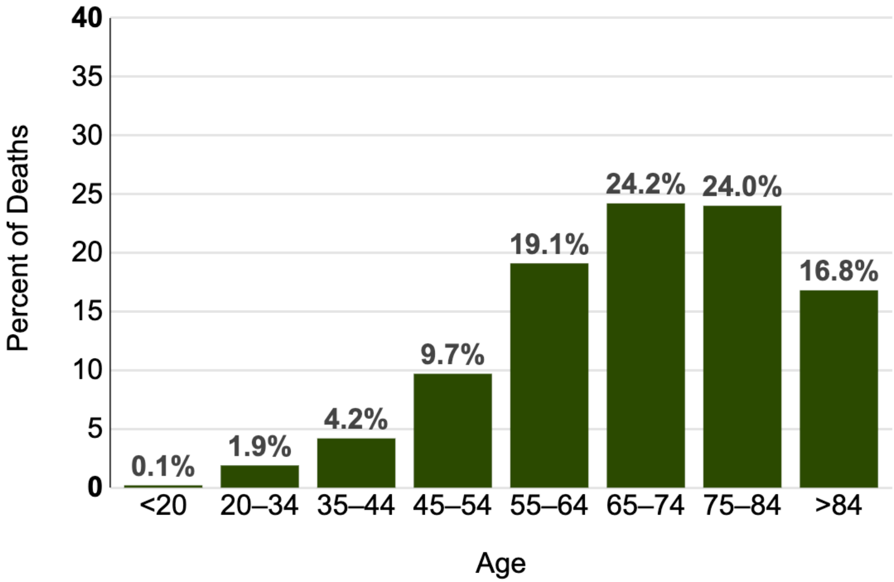
  - Can be deadly for all ages



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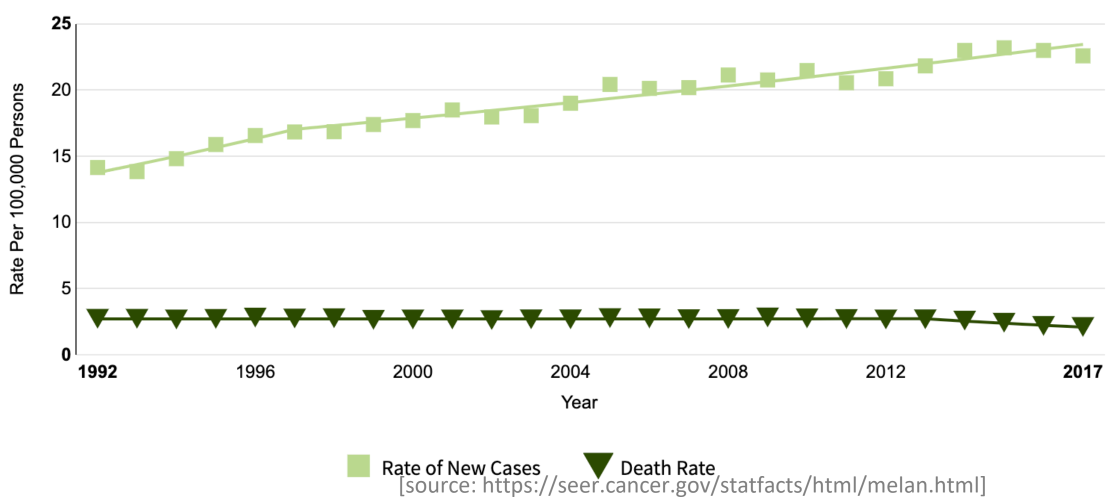
  - Skin cancer: 100.000+ estimated new case 2020
  - Early detection matters
  - Can be deadly for all ages
  - Increasing mortality



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  - Aim
    - Investigate the success of DL models on pattern recognition
    - Measure the robustness of the proposed models
    - As a result: Help physicians to detect melanoma

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    - Investigate the success of DL models on pattern recognition
    - Measure the robustness of the proposed models
    - As a result: Help physicians to detect melanoma
  - Scope
    - Evaluate RGB dermoscopy images in various dimensions
    - Adapt state of the art models to skin lesion problem
      - MultiResUNet, SegAN
    - Compare the results with a well-known benchmark: U-Net
    - Test the accuracy in non trained noisy data
    - Prove if SegAN is more resistant to noise

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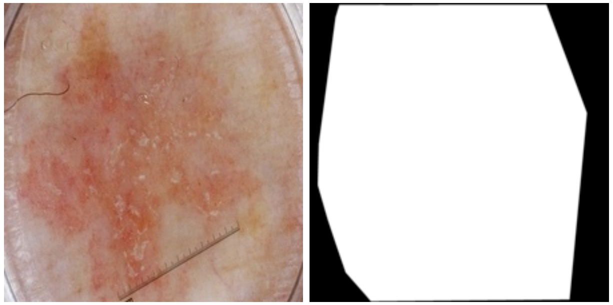
Motivation

- Challenges
  - For physicians
    - Artifacts
      - Moles, freckles, hair, shading, noise
    - Irregular, fuzzy lesion border
    - Low contrast between lesion and surrounding skin
    - Multiple skin lesion



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- Challenges
  - For physicians
    - Artifacts
      - Moles, freckles, hair, shading, noise
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    - Low contrast between lesion and surrounding skin
    - Multiple skin lesion
  - For data scientists
    - Data collection & preparation
    - Implementation of neural networks
    - Hardware requirements

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  - Large datasets
    - MNIST, CIFAR-10, COIL, ImageNet, MS COCO, Flickr,

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  - Large datasets
    - MNIST, CIFAR-10, COIL, ImageNet, MS COCO, Flickr,
  - Increased computational power
    - GPU, TPU
  - Efficient, optimized algorithms; networks
  - Easy to use frameworks
    - Tensorflow, Keras, PyTorch, Caffe

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Image Segmentation Architectures

- Image Segmentation
- Classical Methods
- Brief history of DL
- Common Image Segmentation Architectures

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Image Segmentation Architectures

- Image Segmentation
  - Partitioning an image into distinctive subset

a) b) c)

Image Segmentation Architectures

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Image Segmentation Architectures

- Classical Methods
  - Similarity detection based approach (Region)
    - Thresholding, region growing, region splitting and merging, clustering, watershed

Image Segmentation Architectures

- Classical Methods
  - Similarity detection based approach (Region)
    - Thresholding, region growing, region splitting and merging, clustering, watershed
  - Discontinuity detection based approaches (Edge)
    - Edge detection
      - Sobel, Canny, Laplacian

Image Segmentation Architectures

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Image Segmentation Architectures

- Brief history of DL
  - Milestones
    - Artificial Neural Networks
    - Convolutional Neural Networks
    - Fully Convolutional Networks
  - Is it a blackbox?

Image Segmentation Architectures

- Brief history of DL
  - Milestones
    - Artificial Neural Network
      - Ivakhnenko and Lapa in 1965
      - Remarkable results between 2009 – 2012
        - pattern recognition and machine learning*

*[source: Schmidhuber, J. (2015). "Deep Learning in Neural Networks: An Overview". *Neural Networks*. **61**: 85–117.]

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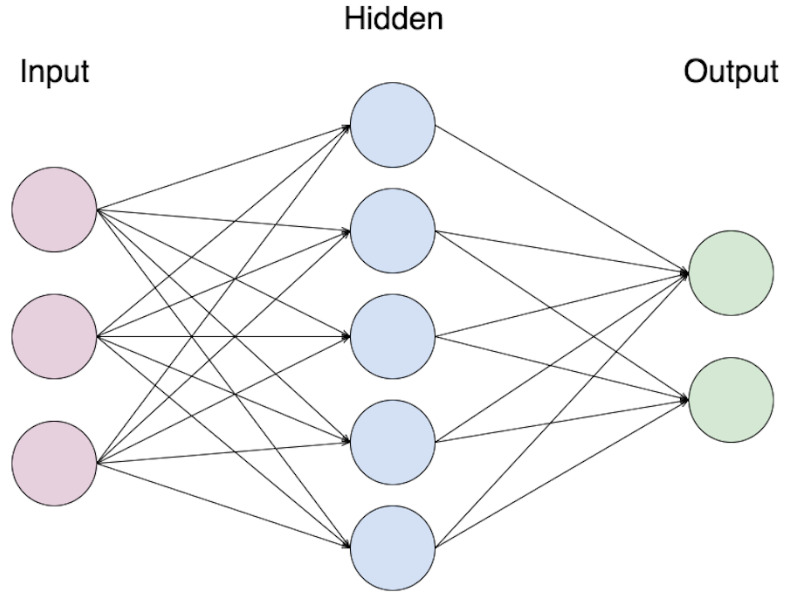

Image Segmentation Architectures

- Brief history of DL
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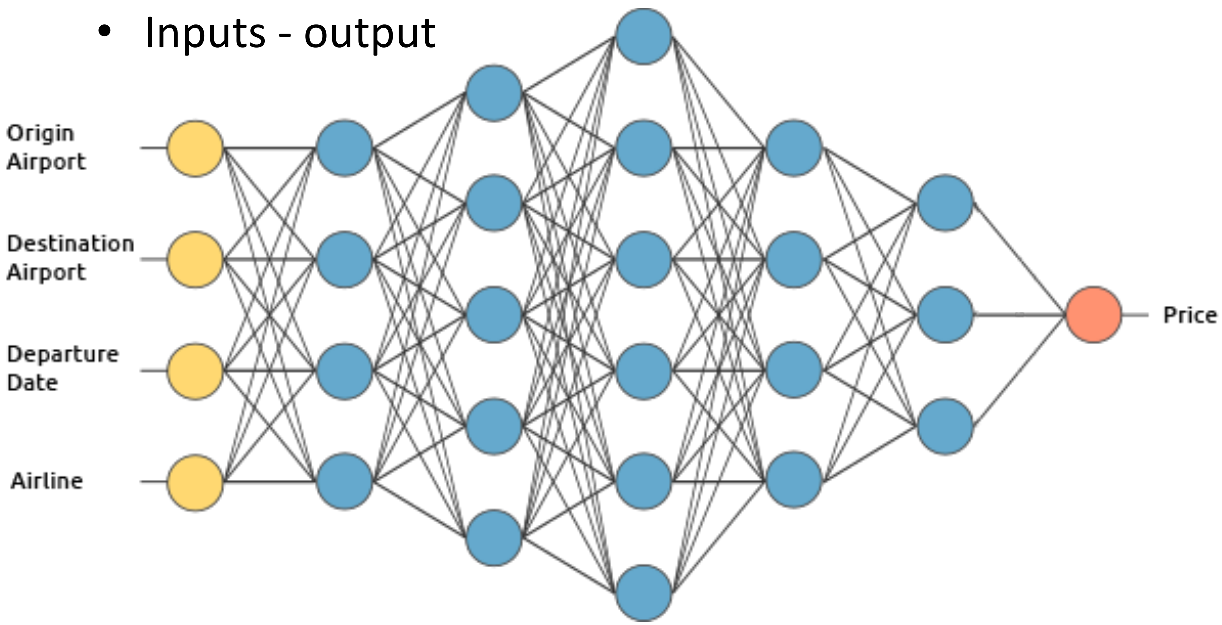
    - Artificial Neural Network
      - Inputs - output



[source: https://cs231n.github.io/neural-networks-1/]

Image Segmentation Architectures

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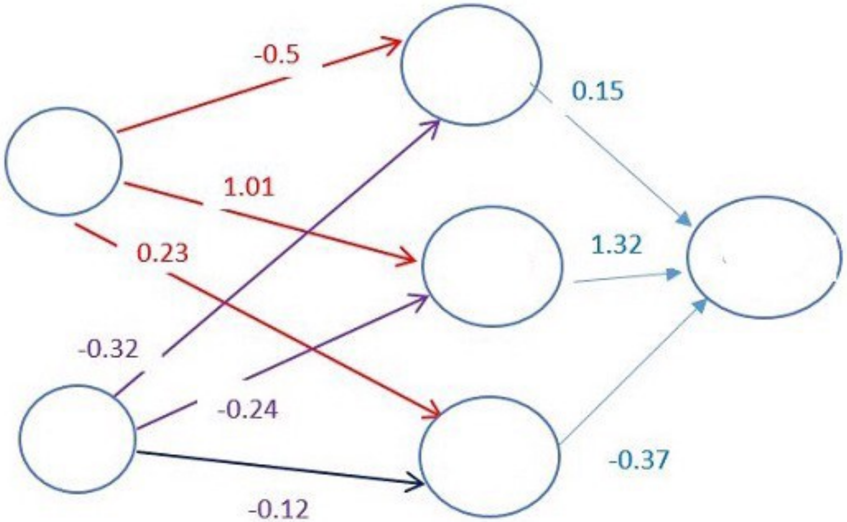
    - Artificial Neural Network
      - Weights



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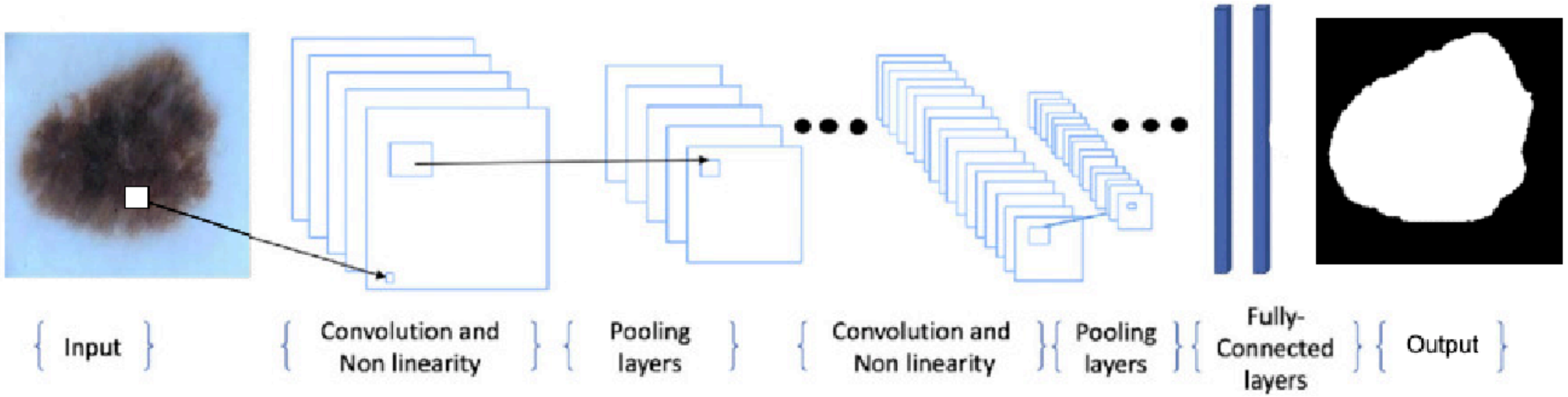

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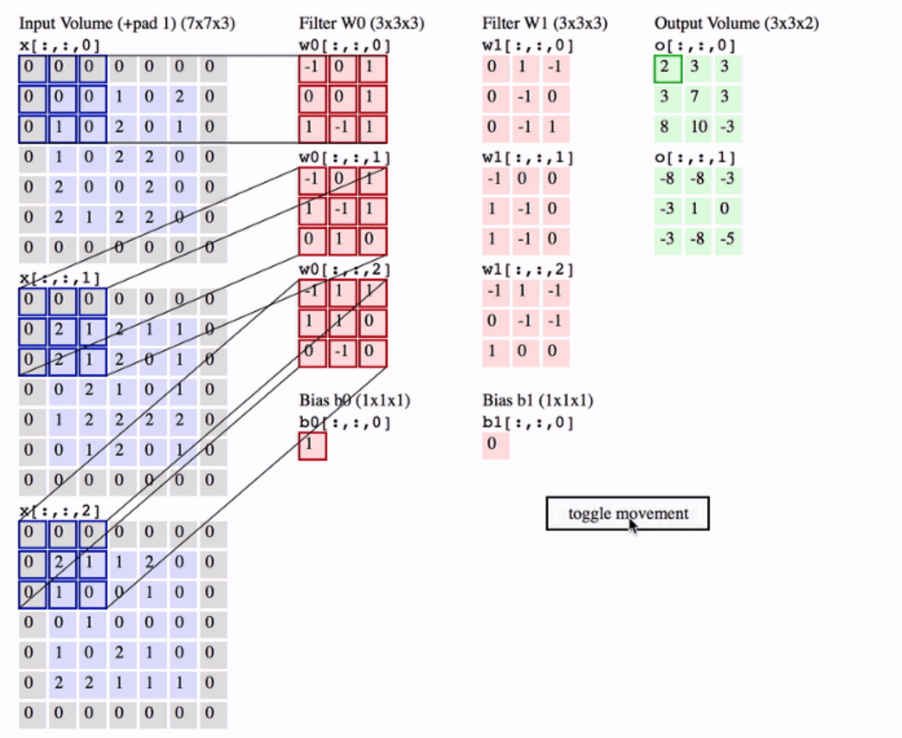

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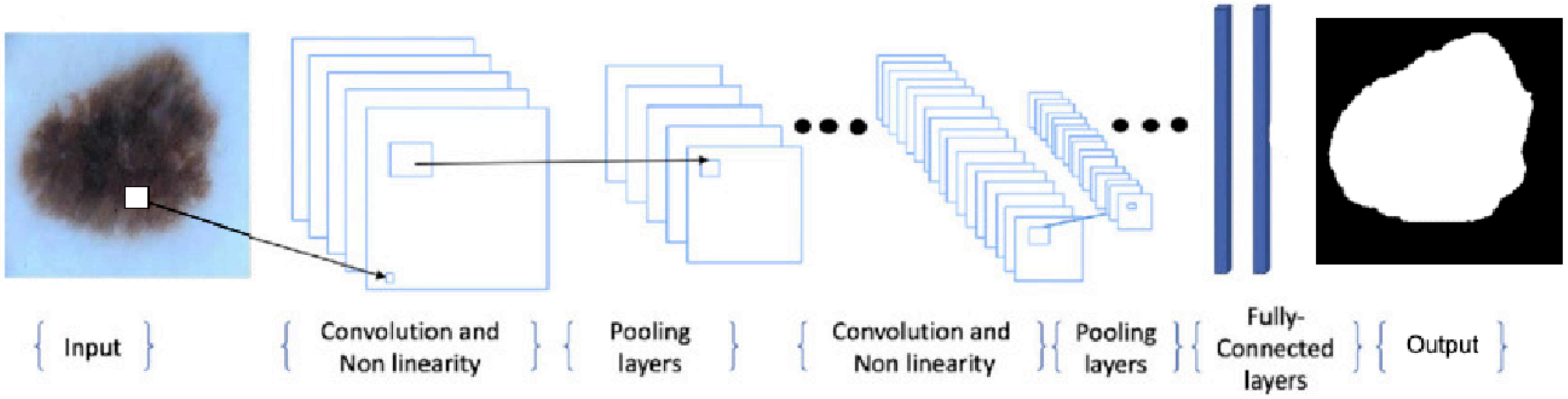

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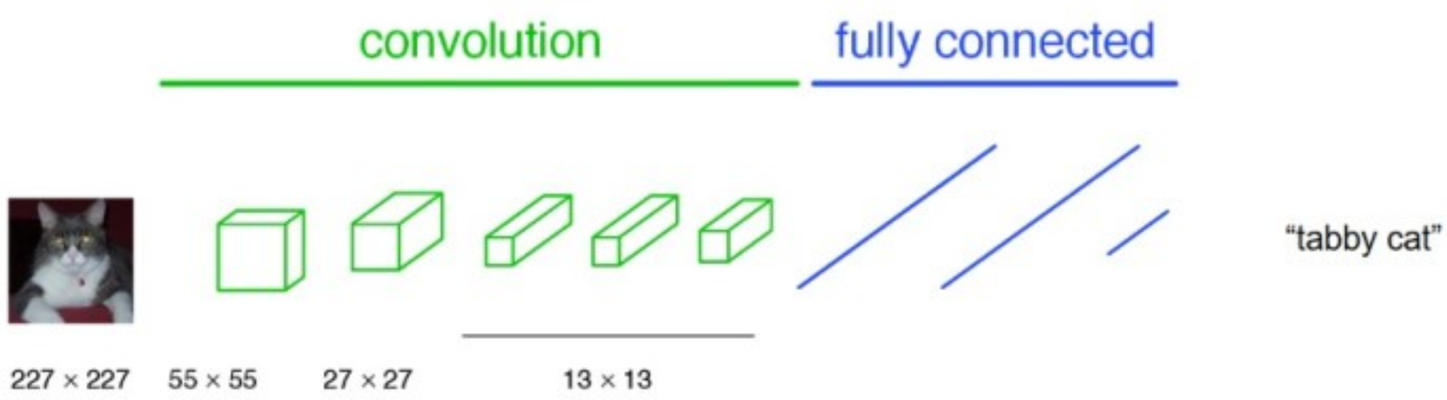
    - Fully Convolutional Networks



[source: https://yapayzeka.ai/semantik-bolutleme-fcn/]

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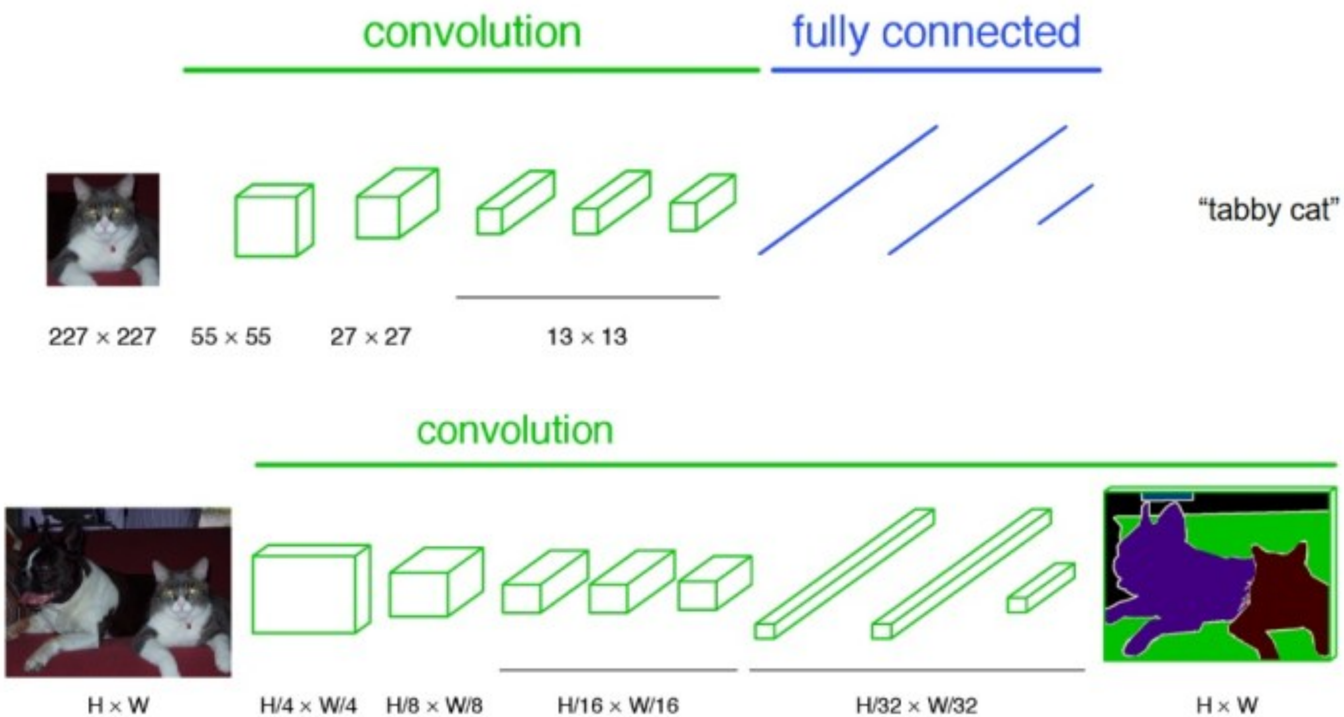

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  - Is it a blackbox?
    - Not easy to follow
      - Hidden layers

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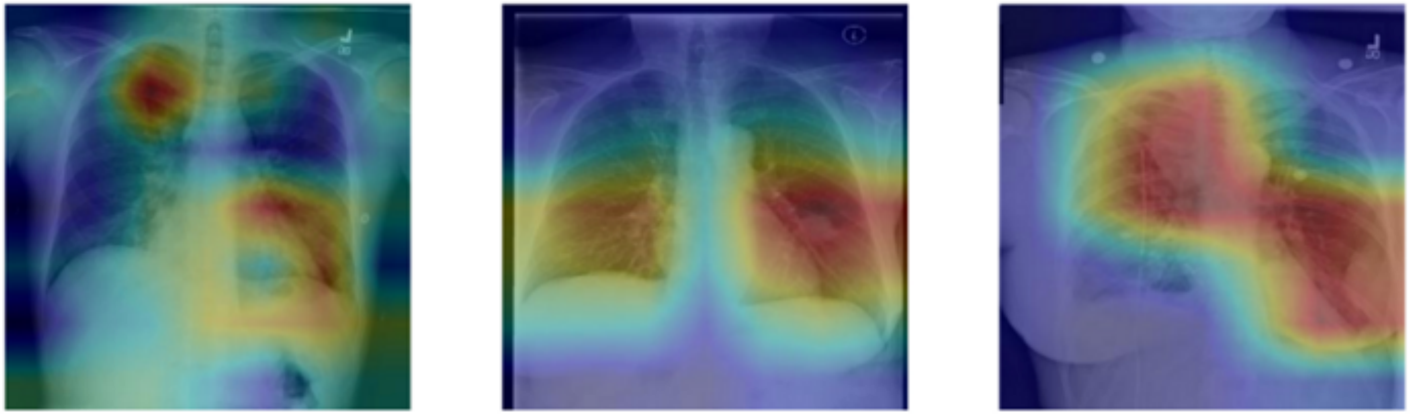
  - Is it a blackbox?
    - Not easy to follow
      - Hidden layers
    - Heat maps



[source: https://arxiv.org/abs/1610.02391]

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Image Segmentation Architectures

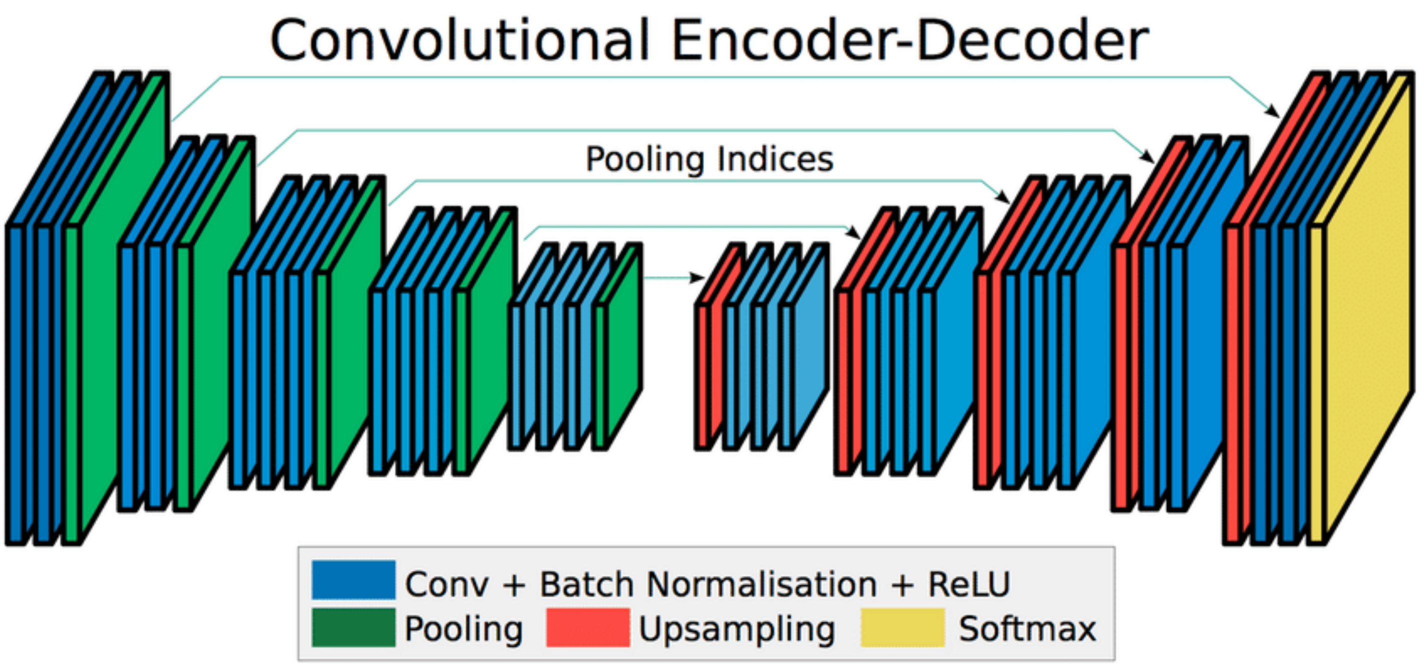
- Common Image Segmentation Architectures
  - Fully Convolutional Network
  - SegNet
  - U-Net
  - Generative Adversial Network (GAN)

Image Segmentation Architectures

- Fully Convolutional Network

Image Segmentation Architectures

- SegNet
  - Semantic segmentation



[source: Trokielewicz, Mateusz, and Adam Czajka. "Data-driven segmentation of post-mortem iris images." 2018 International Workshop on Biometrics and Forensics (IWBF). IEEE, 2018]

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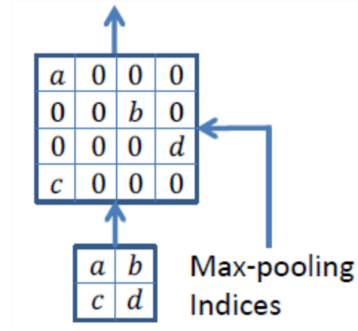

Upsampling Using Max-Pooling Indices

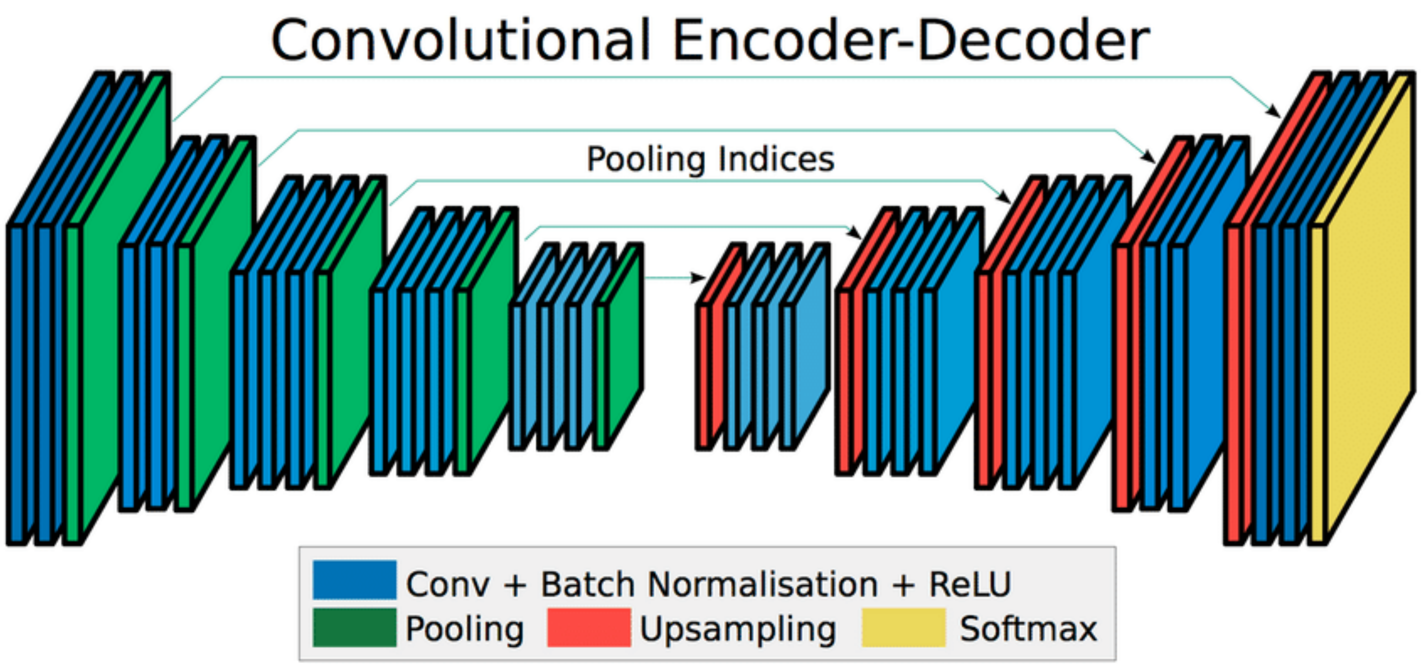

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Image Segmentation Architectures

- U-Net
  - Ronneberger, Fischer, and Brox, 2015
  - Medical image segmentation

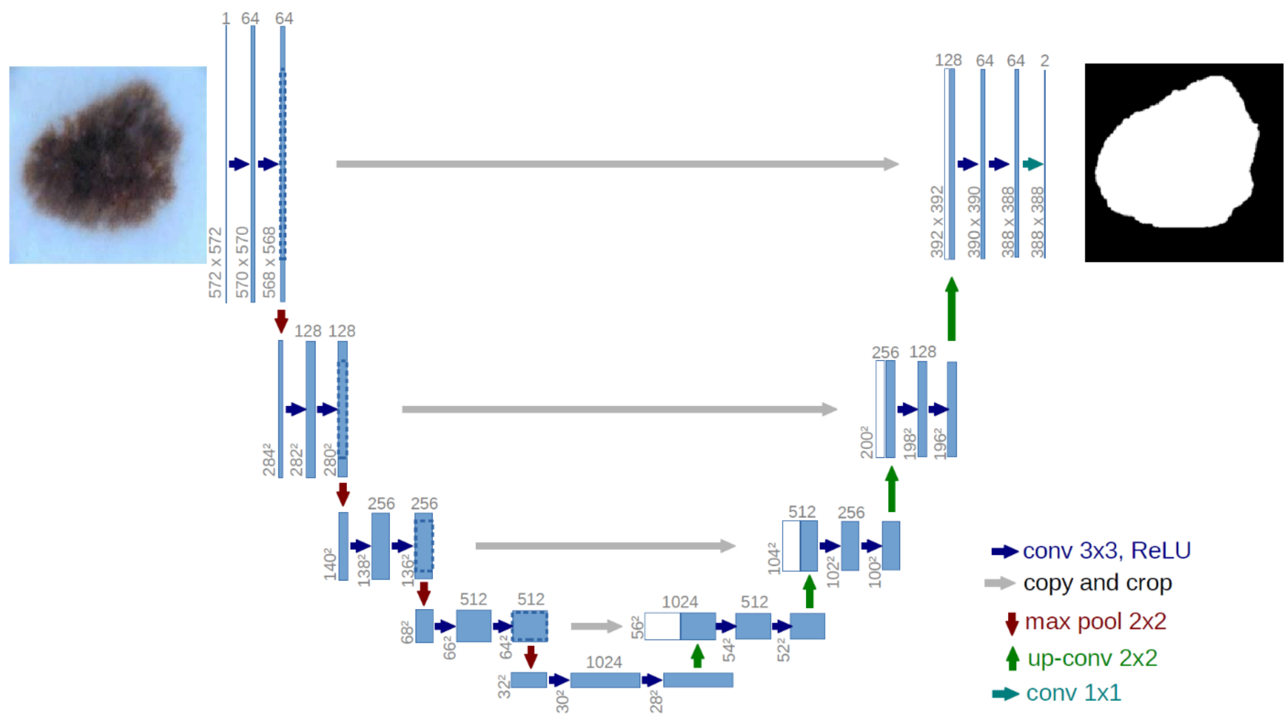
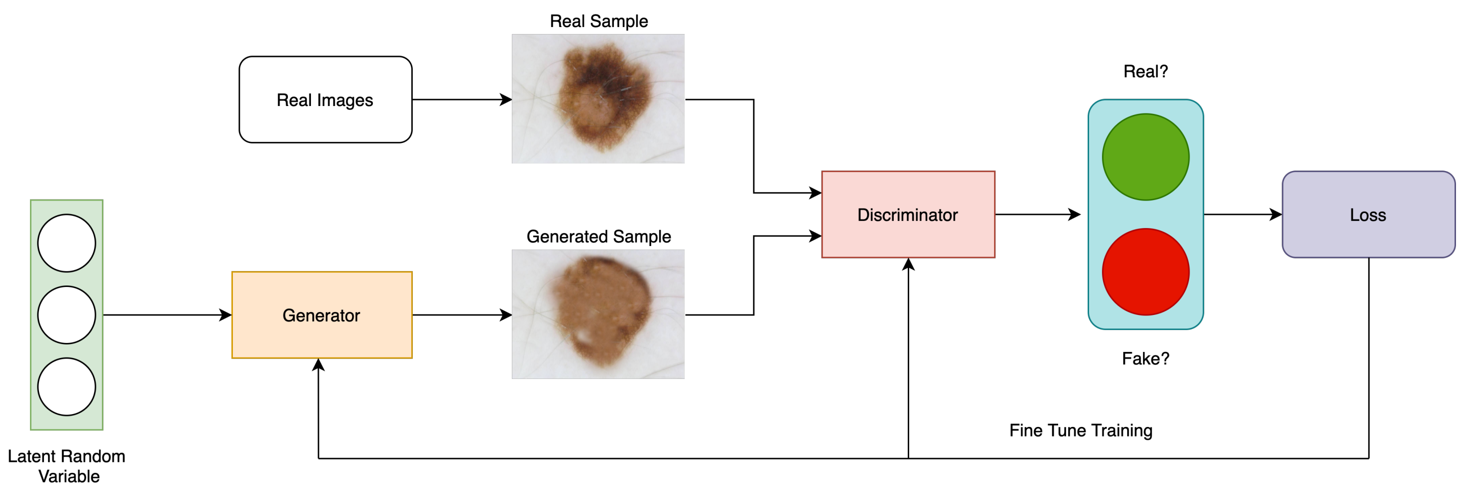


Image Segmentation Architectures

- Generative Adversial Network (GAN)
  - Goodfellow, 2014



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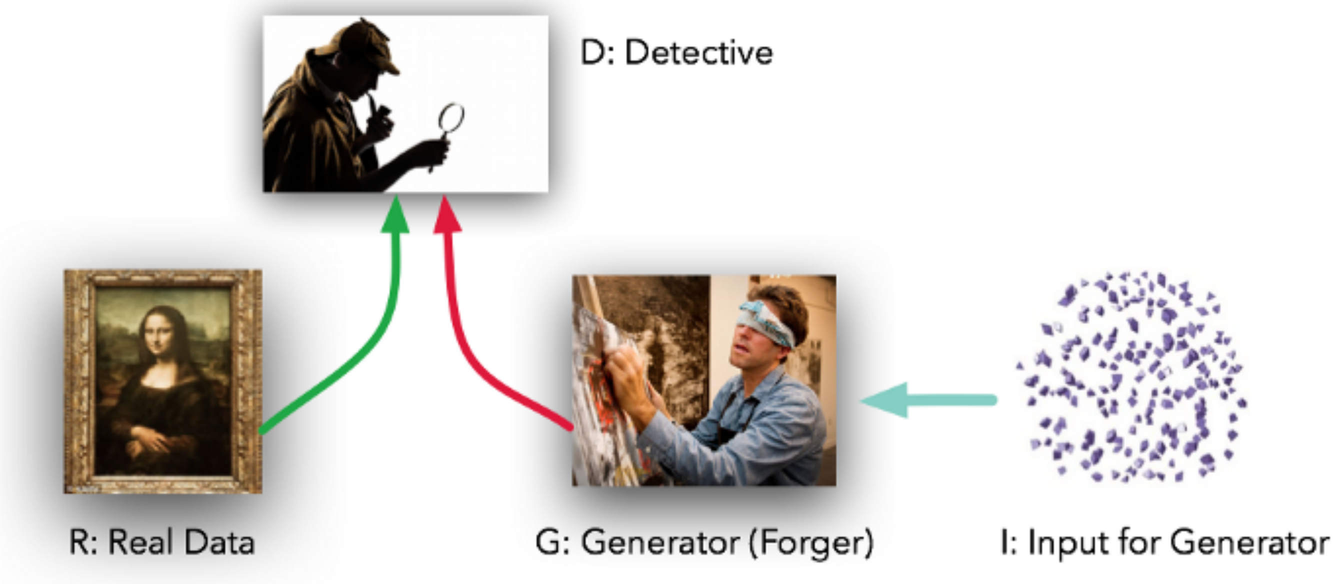

Source : https://medium.com/@devnag/generative-adversarial-networks-gans-in-50-lines-of-code-pytorch-e81b79659e3f

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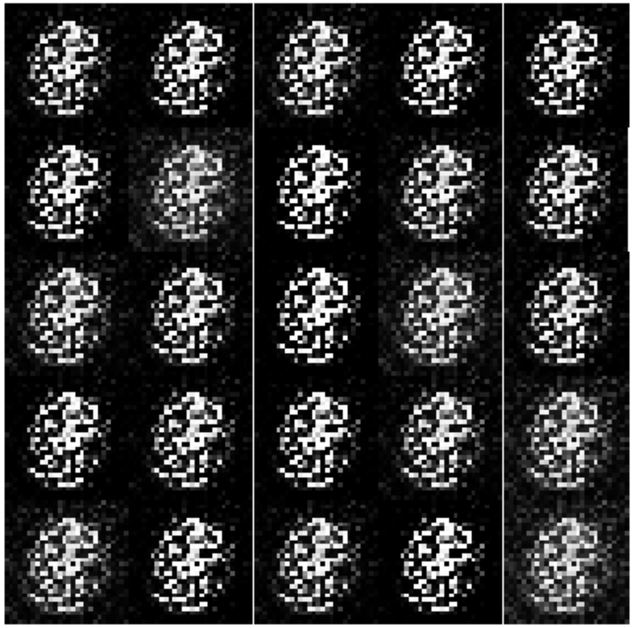

Epoch 1

Source : https://github.com/togheppi/vanilla_GAN

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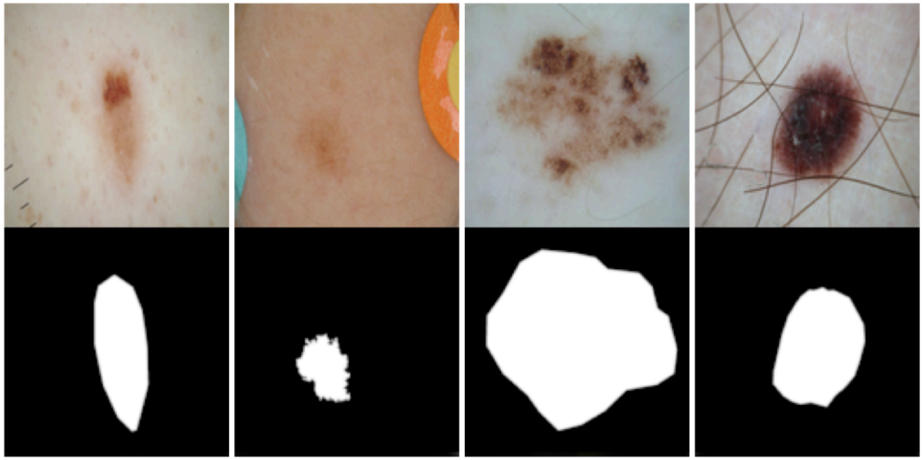
  - 2750 **RGB images** with **binary masks** in different resolutions
    - 2000 train
    - 600 test
    - 150 validation



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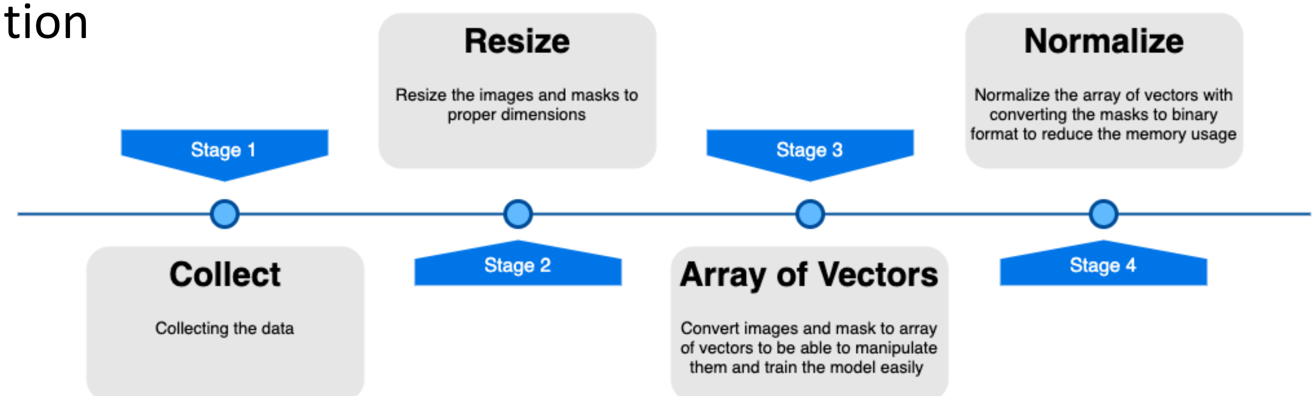

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- Dataset
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Methodology

- Networks
  - MultiResUNet
  - SegAN
  - U-Net
    - Benchmark

Methodology

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  - U-Net
- Why these networks?

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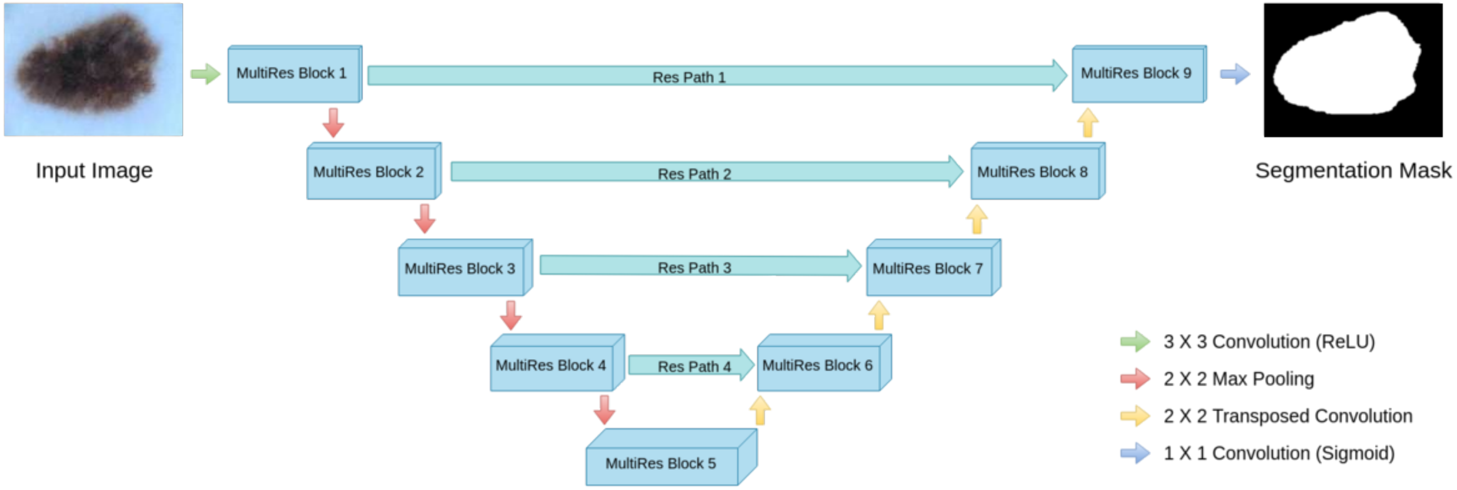
    - GAN based segmentation architectures is not common
      - The first GAN based segmentation architecture
    - Not trained with the dermoscopy images

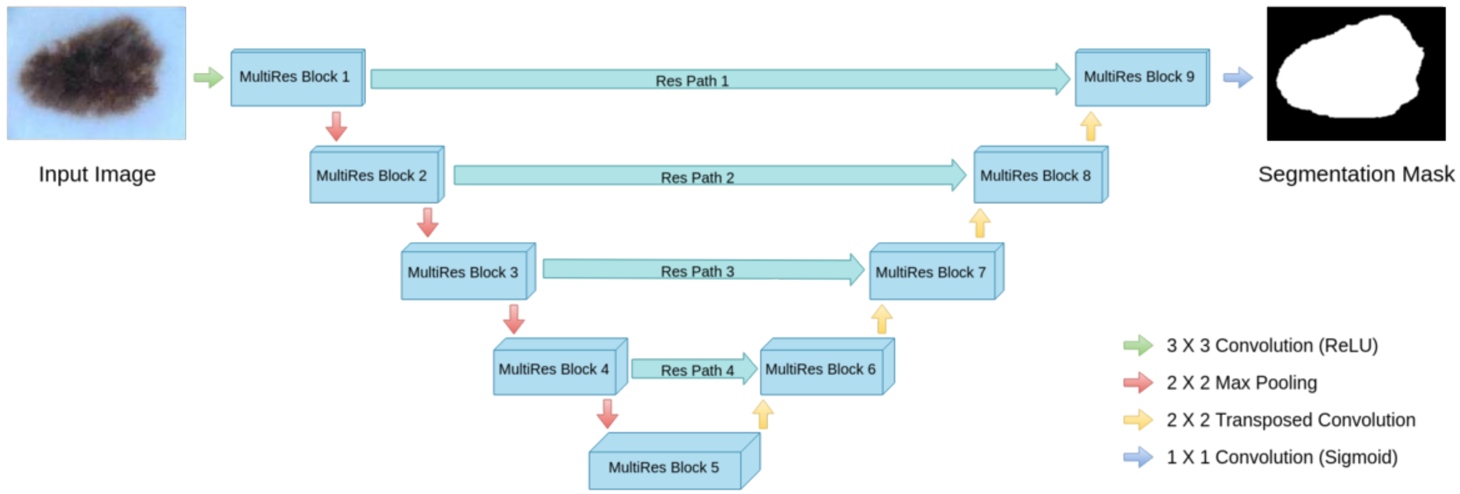
Methodology

- Networks
  - MultiResUNet



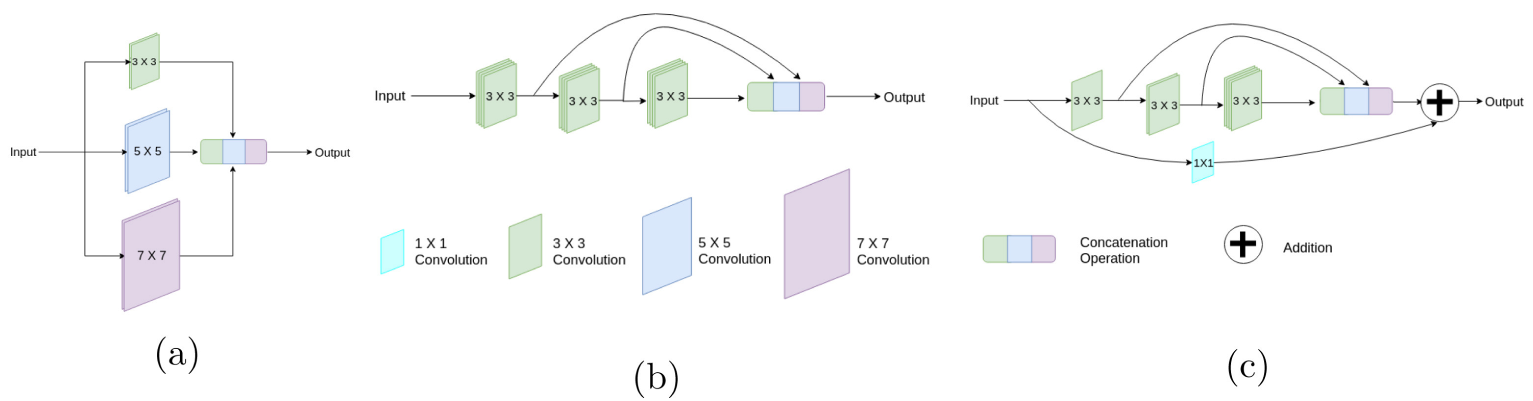
Methodology

- Networks
  - MultiResUNet
    - Updated UNet: MultiRes Blocks + Res Paths



Methodology

- Networks
  - MultiResUNet
    - MultiRes Block



Evalution of MultiRes block : (a) Inception-like block (b) a more expensive attempt (c) MultiRes block

[source: Ibtehaz, Nabil, and M. Sohel Rahman. "MultiResUNet: Rethinking the U-Net architecture for multimodal biomedical image segmentation." Neural Networks 121 (2020): 74-87.]

Methodology

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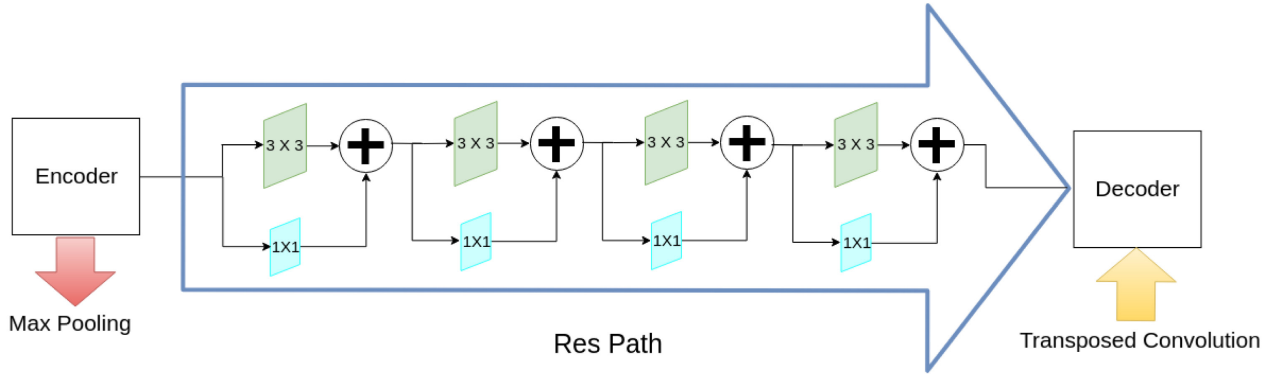
  - MultiResUNet
    - Res Path



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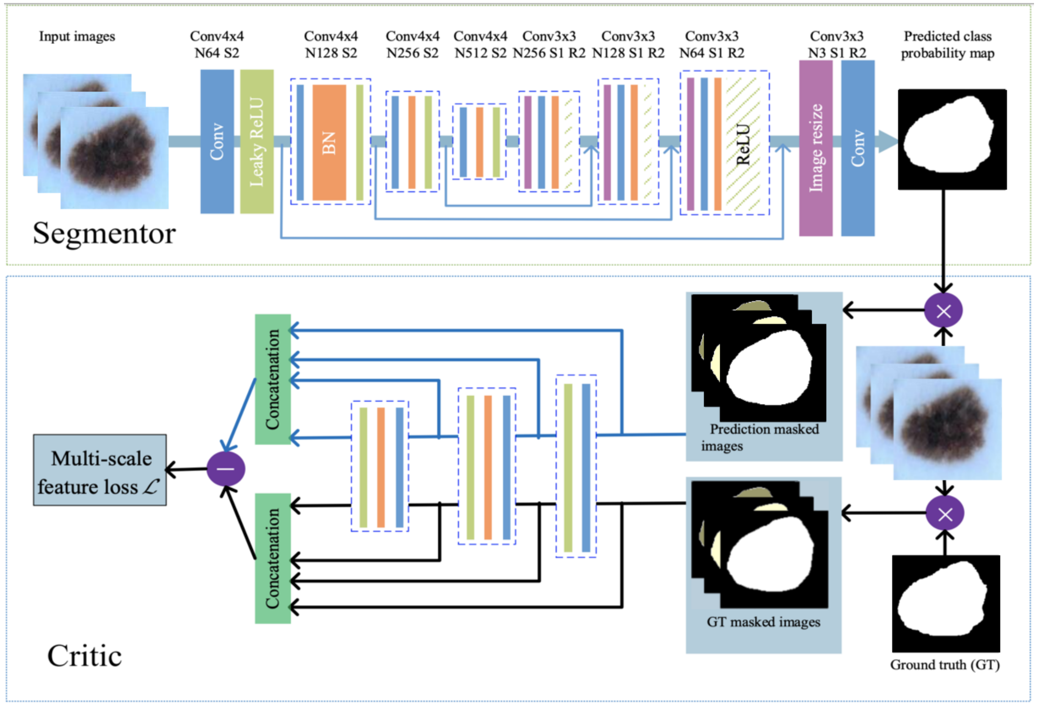

Methodology

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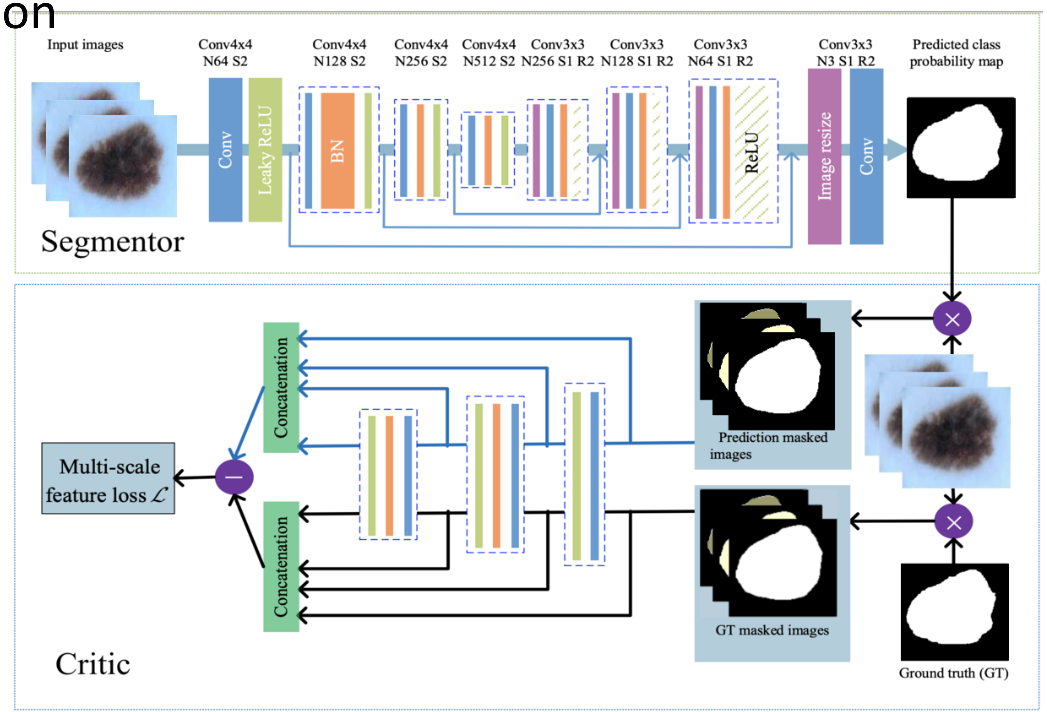
    - Multi-scale loss function



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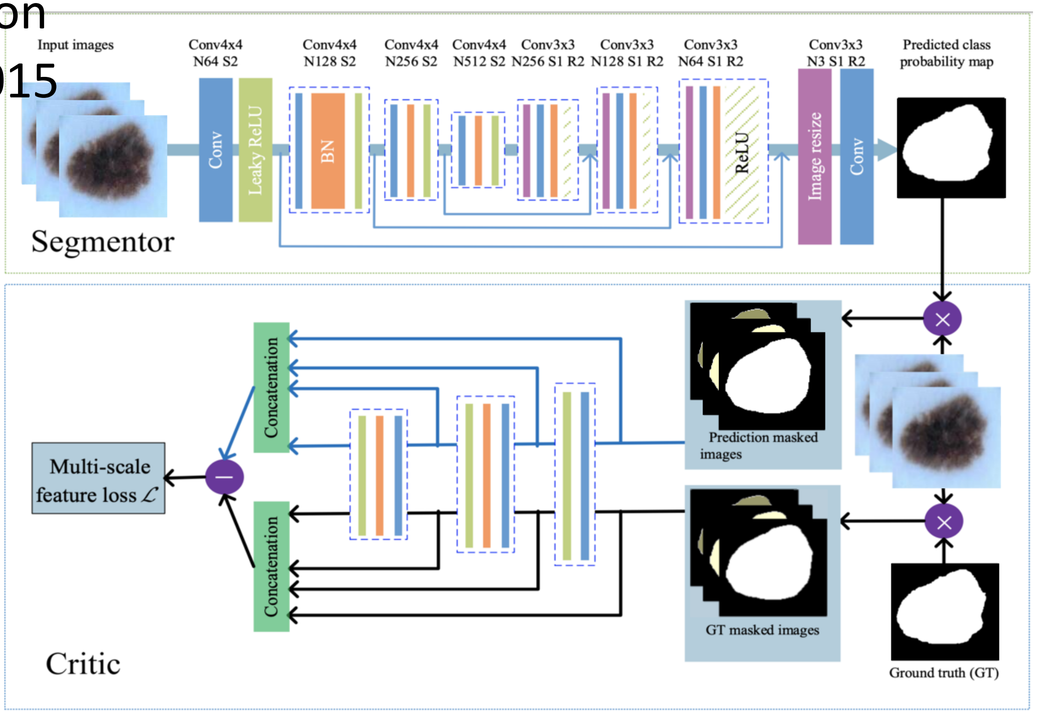
    - Comparet to BRATS 2015



Methodology

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Methodology

- Tools and Frameworks
  - Tools
    - Numpy: Scientific computing library
    - PIL: Image manipulating, filtering, masking etc.
    - ImageMagick: Image editing with rich morphological operation support
    - Jupyter Notebook: Web app that allows editing, running code with several languages

Methodology

- Tools and Frameworks
  - Deep Learning Frameworks
    - Tensorflow(v2.2.0): A library for performing numerical computations
    - Keras(v2.3.0): Neural network API for Python which can be run on top of TensorFlow or Theano
    - Pytorch(v1.5.1): Easy to use machine learning framework introduced by Facebook

Methodology

- Tools and Frameworks
  - Hardware Requirements
    - Google Colab
      - Jupyter Notebook environment
      - Runs on the cloud
      - Tesla K80 GPU
        - 25 GB of video memory
      - Ubuntu 18.04

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Methodology

- A quick reminder before experiments
  - Hyperparams
    - Epoch
    - Batch size
    - Loss function
    - Optimizer
  - Early stopping
  - Gaussian noise

$$p_G(z) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(z-\mu)^2}{2\sigma^2}}$$

Gaussian noise distribution in single channel image: μ and σ represents the mean value and the standard deviation, respectively

Methodology

- Experiments
  - Hyperparams
    - MultiResUNet
      - Epoch: 200
      - Batch size: 8
      - Loss function: Binary cross entropy
      - Optimizer: Adam
    - SegAN
      - Epoch: 200
      - Batch size: 8
      - Loss function: Proposed multi-scale loss function
      - Optimizer: Adam
  - Early stopping
    - After 25 epoch
  - Different Gaussian noise level
    - σ values from 0 to 50 by 10

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Methodology

- Evaluation Metrics
  - Dice Coefficient (F1 score)
  - Jaccard Index
  - Accuracy
  - Sensitivity (Recall)
  - Specificity

$$Dice = \frac{2 * TP}{2 * TP + FN + FP}$$

Methodology

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$$Jaccard = \frac{TP}{TP + FN + FP}$$

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$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

Methodology

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$$Sensitivity = \frac{TP}{TP + FN}$$

$$Specificity = \frac{TN}{TN + FP}$$

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Results

- Train duration
  - MultiResUnet: ~8 hours
  - SegAN: ~11 hours
  - U-Net: ~8 hours

Results

- Train duration
  - MultiResUnet: ~8 hours
  - SegAN: ~11 hours
    - Two network: Segmentor and Critic
  - U-Net: ~8 hours

Results

- Statistical metrics

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MultiResUNet

Gaussian noise(%)	Dice	Jaccard	Accuracy	Sensitivity	Specificity
0	0.8169	0.7221	0.922	0.964	0.9482
10	0.7707	0.6747	0.9058	0.8923	0.9024
20	0.7395	0.624	0.8829	0.8788	0.8705
30	0.6056	0.4784	0.6056	0.8402	0.7949
40	0.4345	0.3061	0.8062	0.7033	0.8104
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Gaussian noise(%)	Dice	Jaccard	Accuracy	Sensitivity	Specificity
0	0.6437	0.5343	0.8619	0.7350	0.8825
10	0.6156	0.5087	0.8559	0.7562	0.8718
20	0.5584	0.4482	0.8423	0.7680	0.8507
30	0.4746	0.3707	0.8282	0.7817	0.8316
40	0.2562	0.1737	0.7853	0.6236	0.7941
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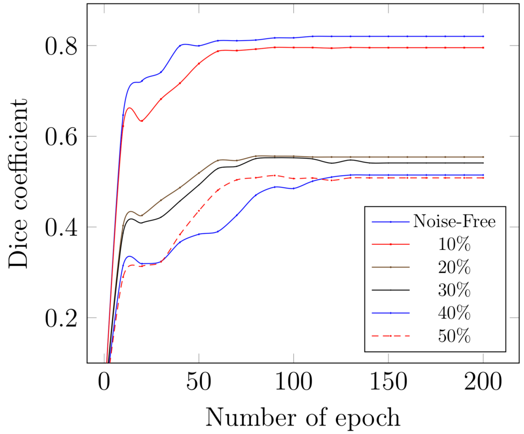
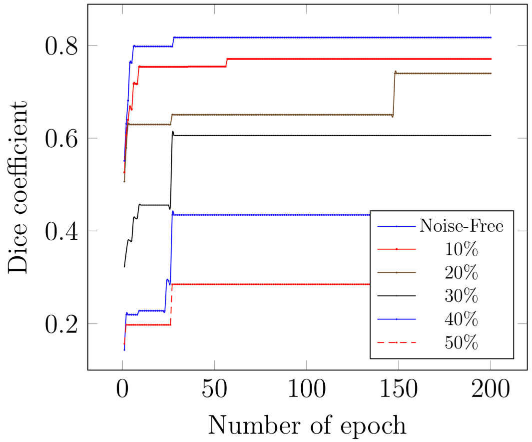
Results

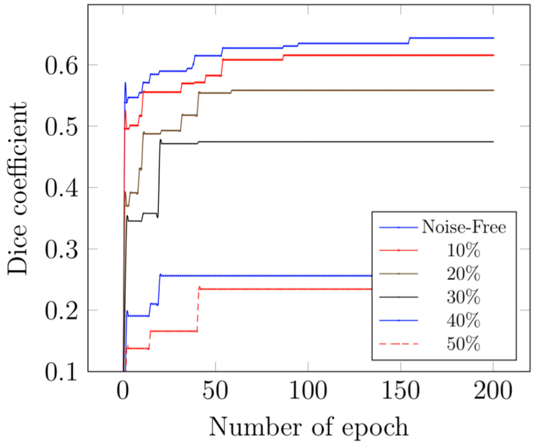
- Dice results at different Gaussian noises by number of epochs



MultiResUNet



SegAN



U-Net

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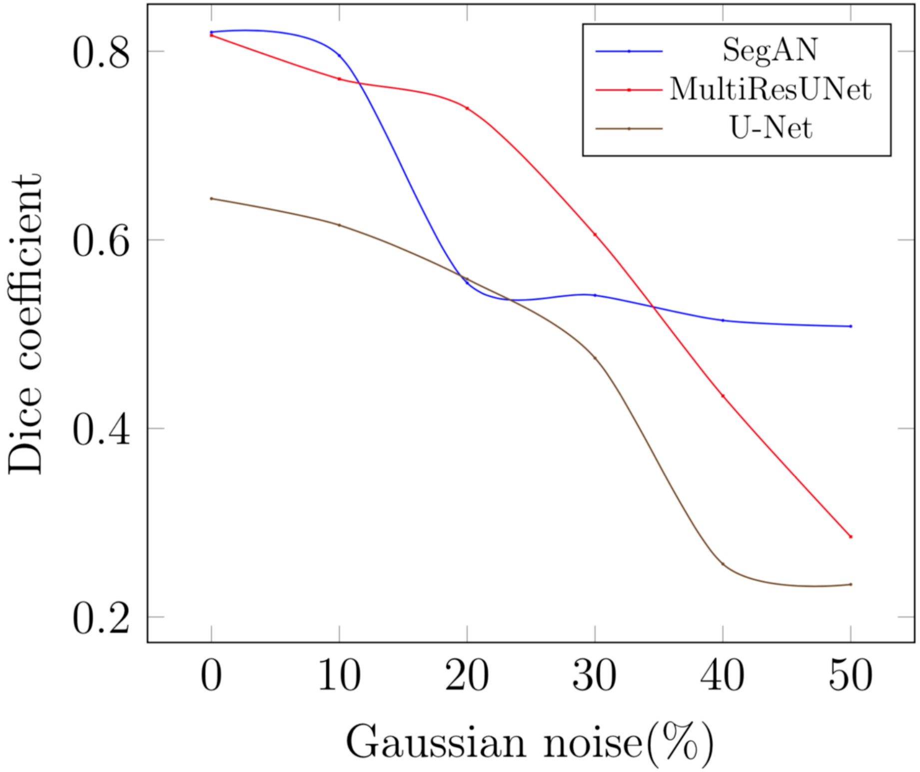
- Comparison of the results of the models at different noise levels



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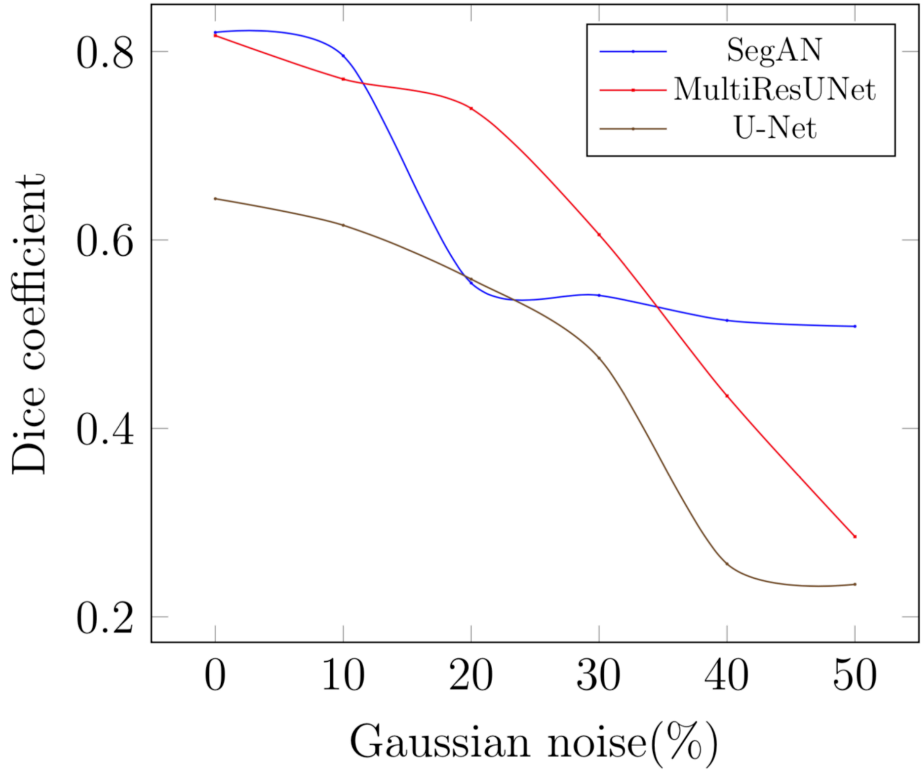
  - The both has similar Dice for noise free images



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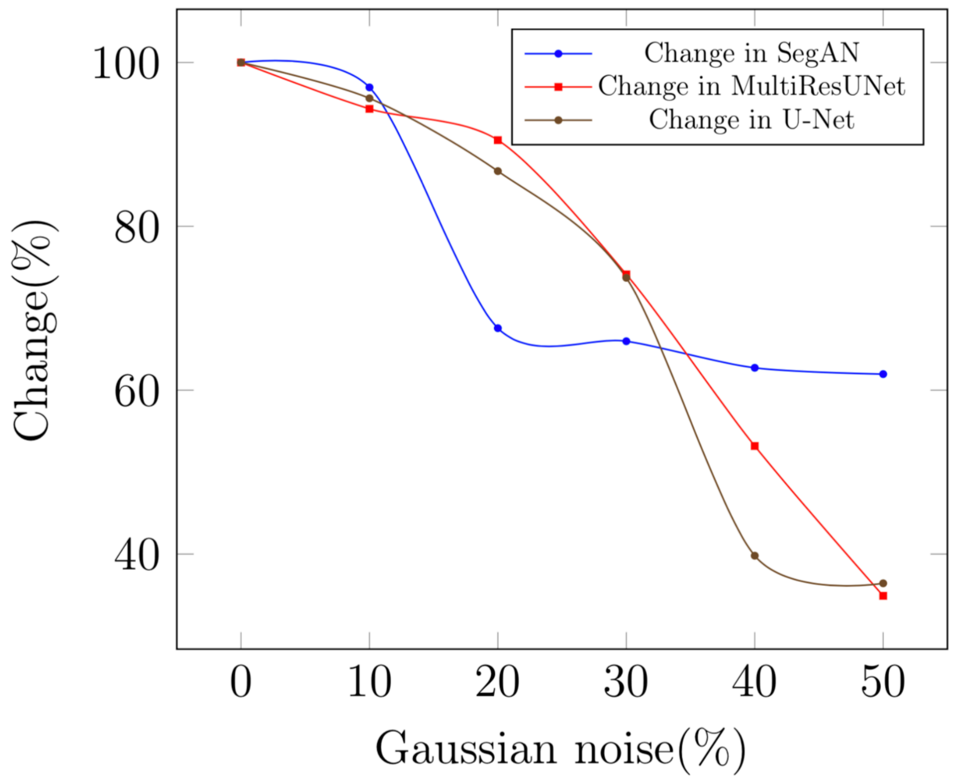

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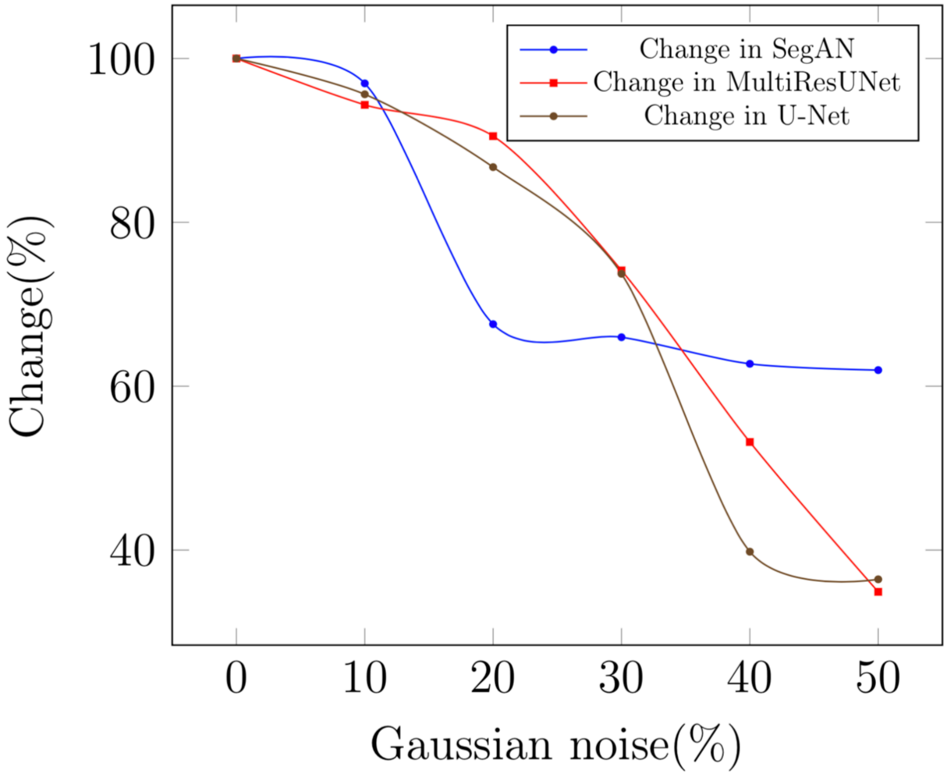

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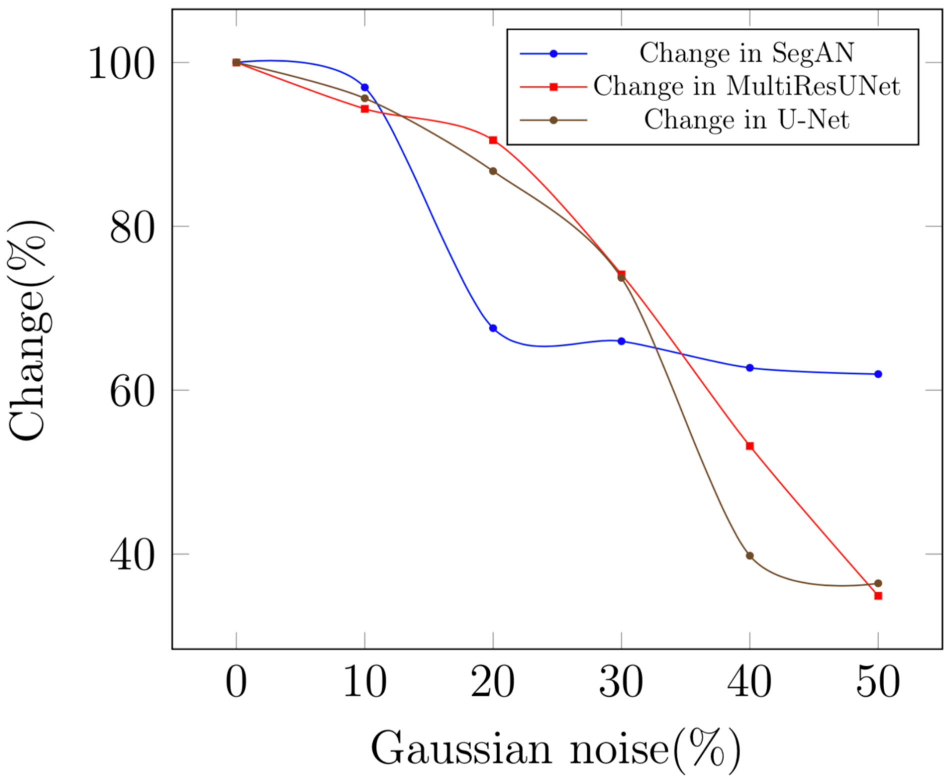
    - Trained with noise



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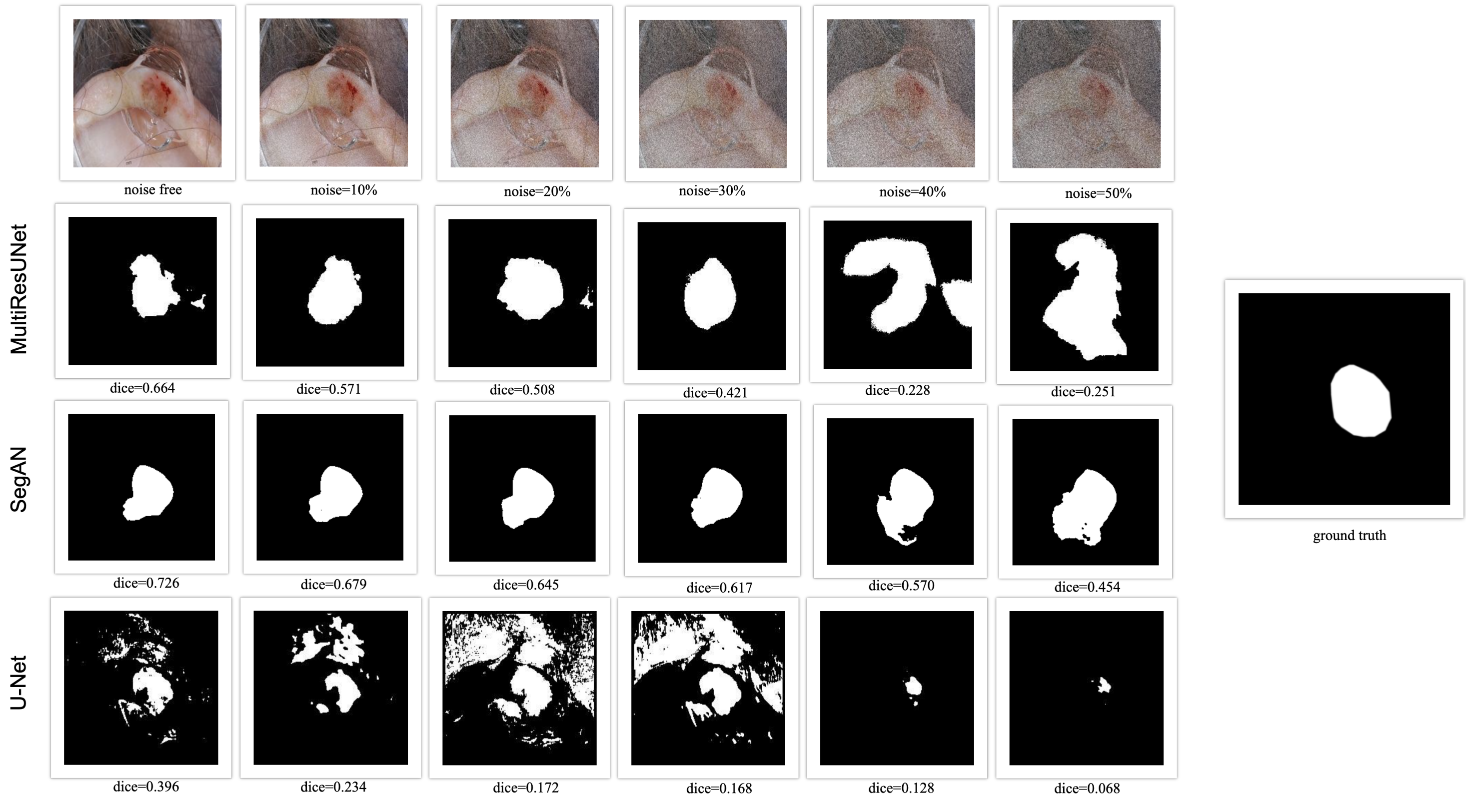

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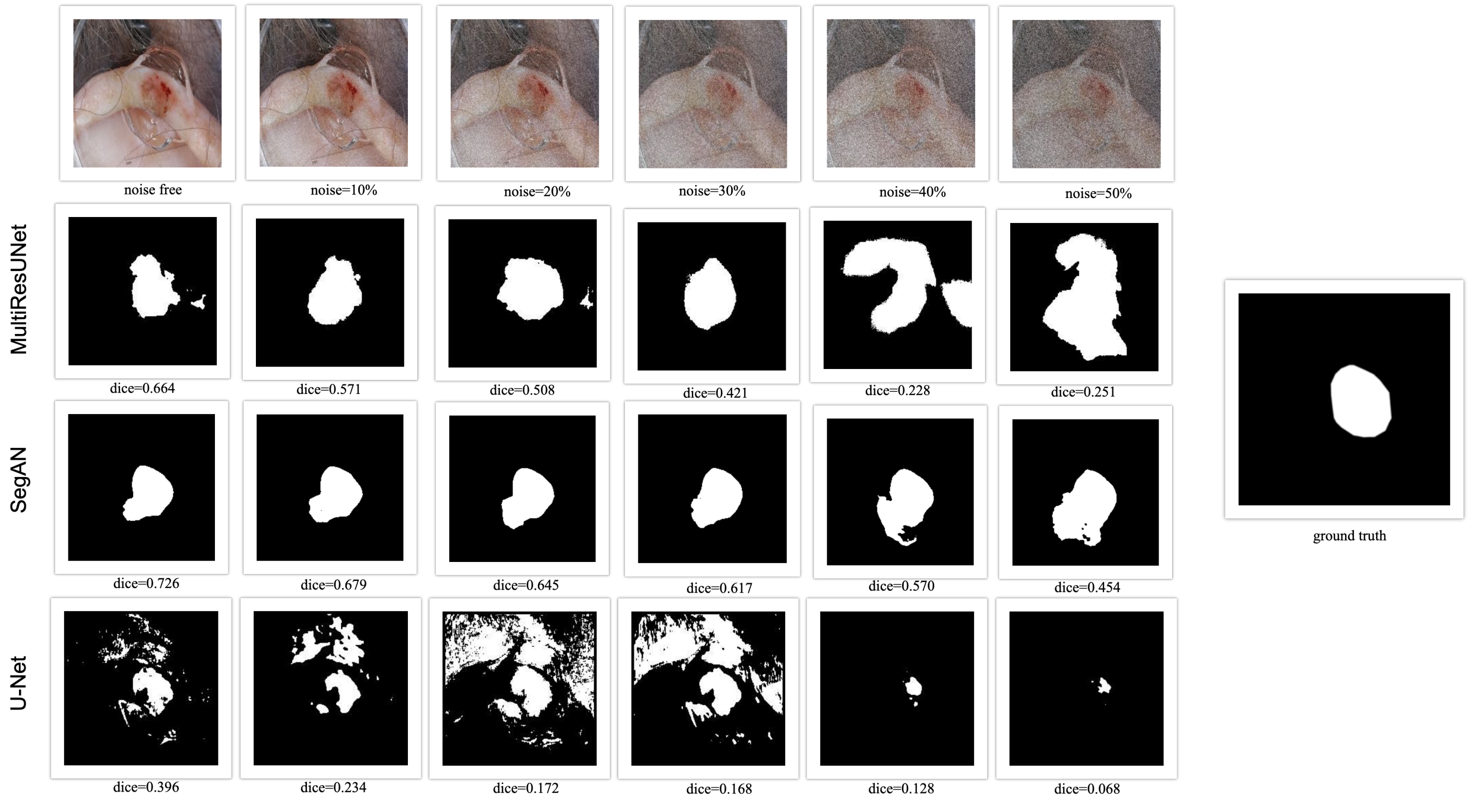

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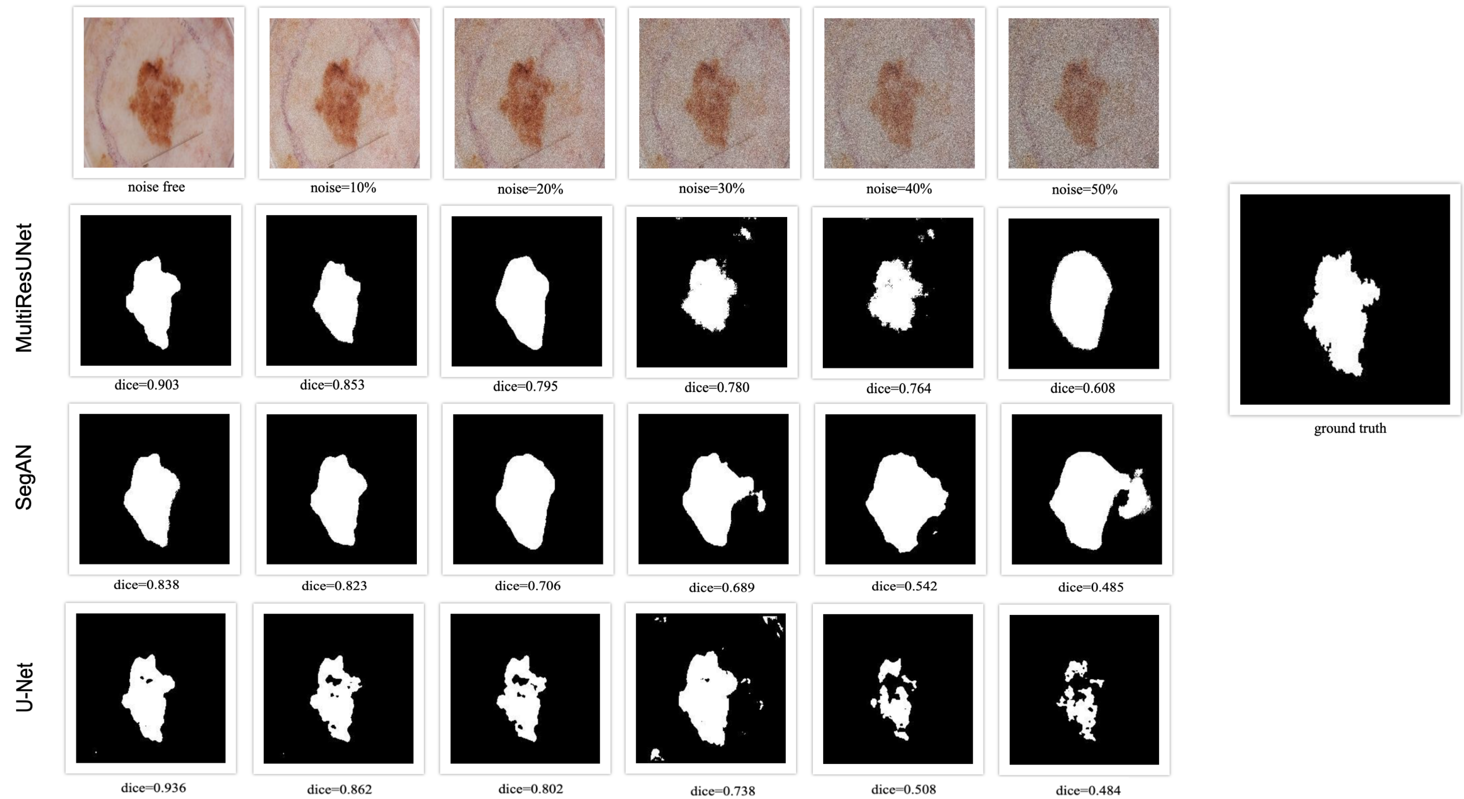

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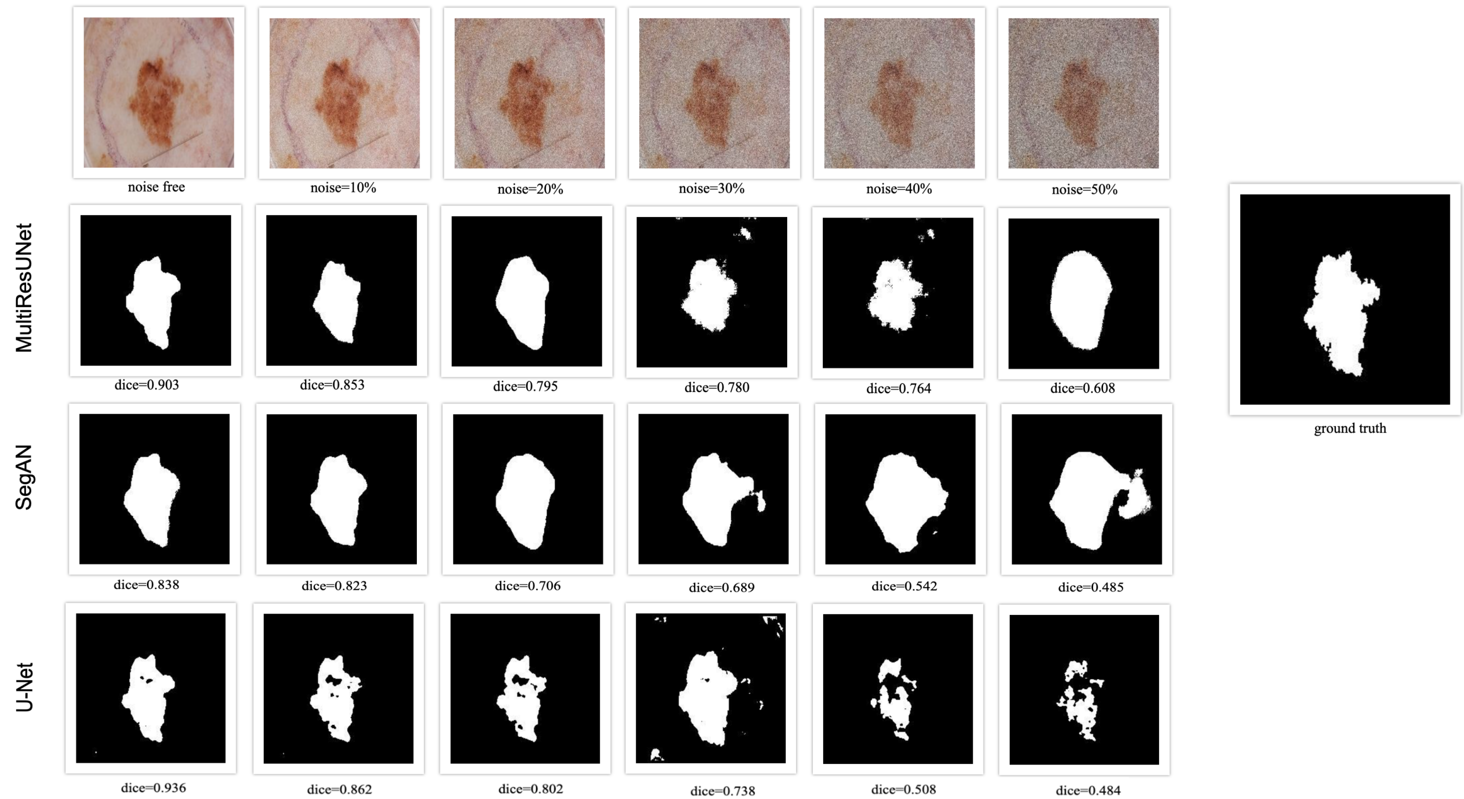

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  - No precise superiority of the models to each other for certain data

Outline

- Motivation
- Image Segmentation Architectures
- Methodology
- Results
- Discussions and Future Works
- Conclusion

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- Visualize with the help of heat maps

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Conclusion

- This thesis addressed to
  - Evaluate RGB dermoscopy images in various dimensions
  - Adapt state of the art models to skin lesion problem
    - MultiResUNet, SegAN
  - Test the accuracy in non trained noisy data
- This thesis showed that
  - Preferred models get remarkable results on the selected dataset
    - ISBI 2017 Challenge
  - SegAN is more resistant to noise against MultiResUNet
  - MultiResUNet can be preferred for noise free data