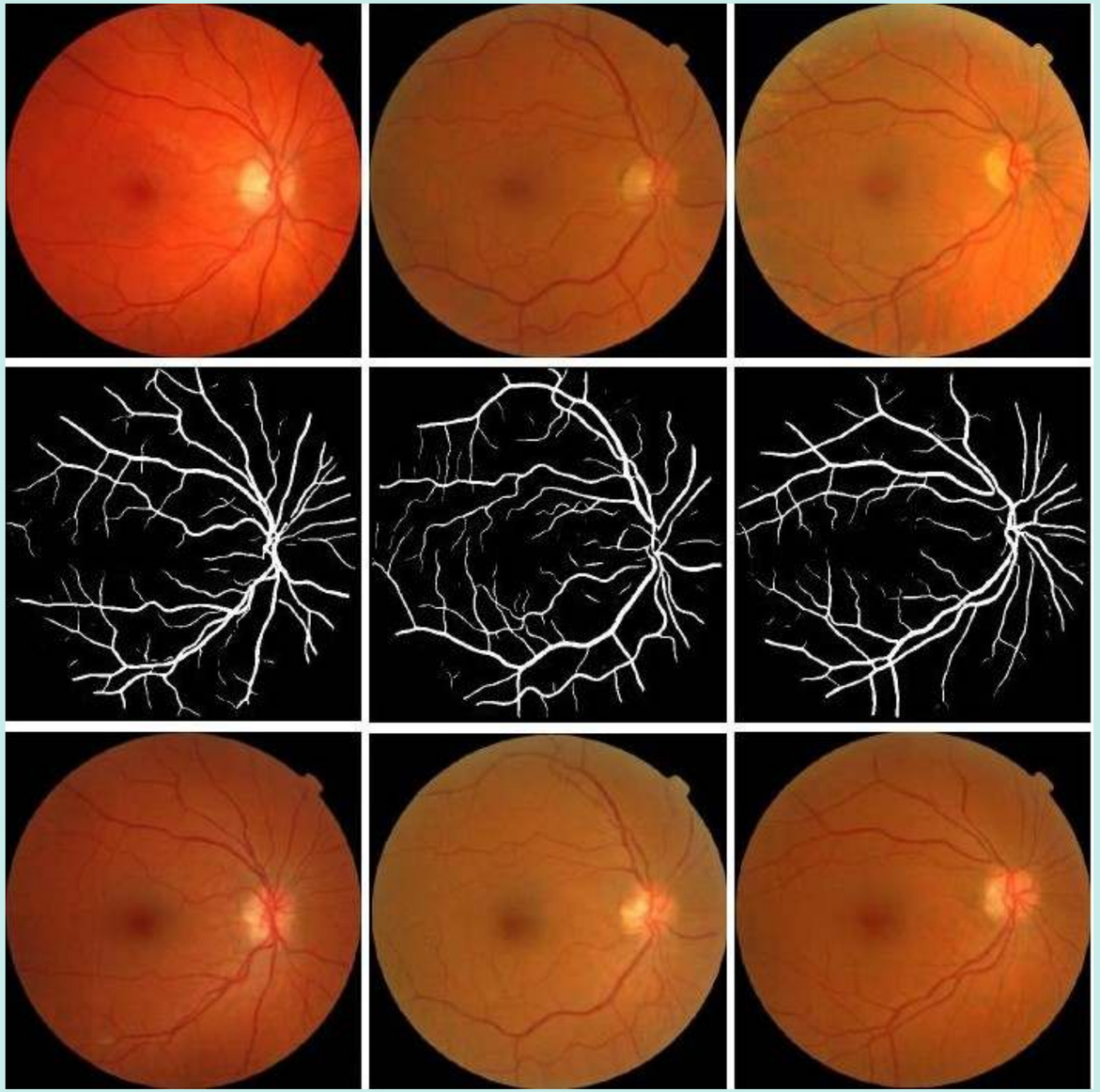
Automated Segmentation of Cell images Using Cycle-Consistent Generative Adversarial Networks

Applied on retinal Pigment Epithelium



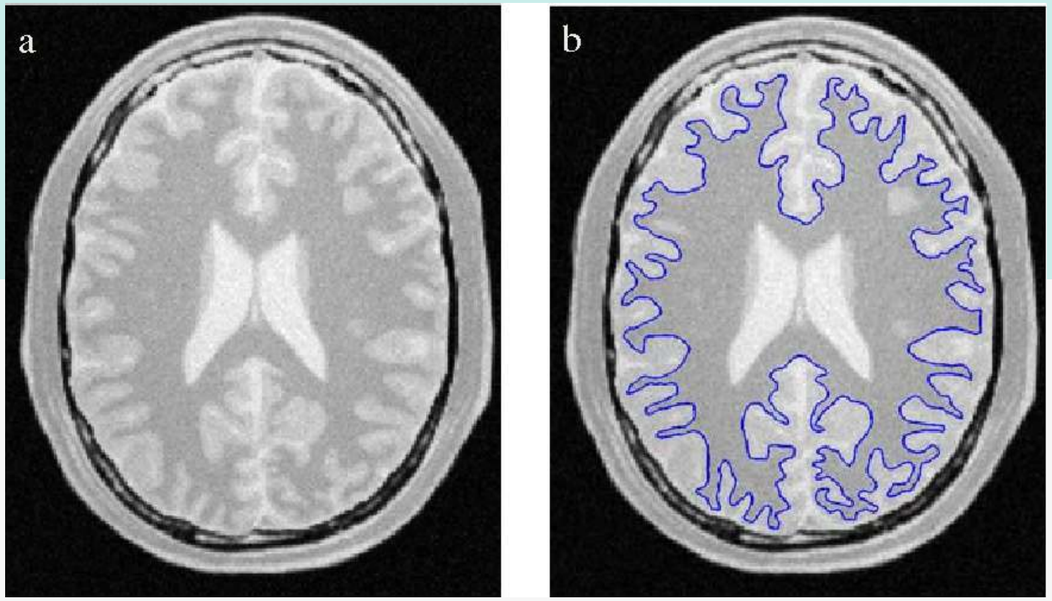
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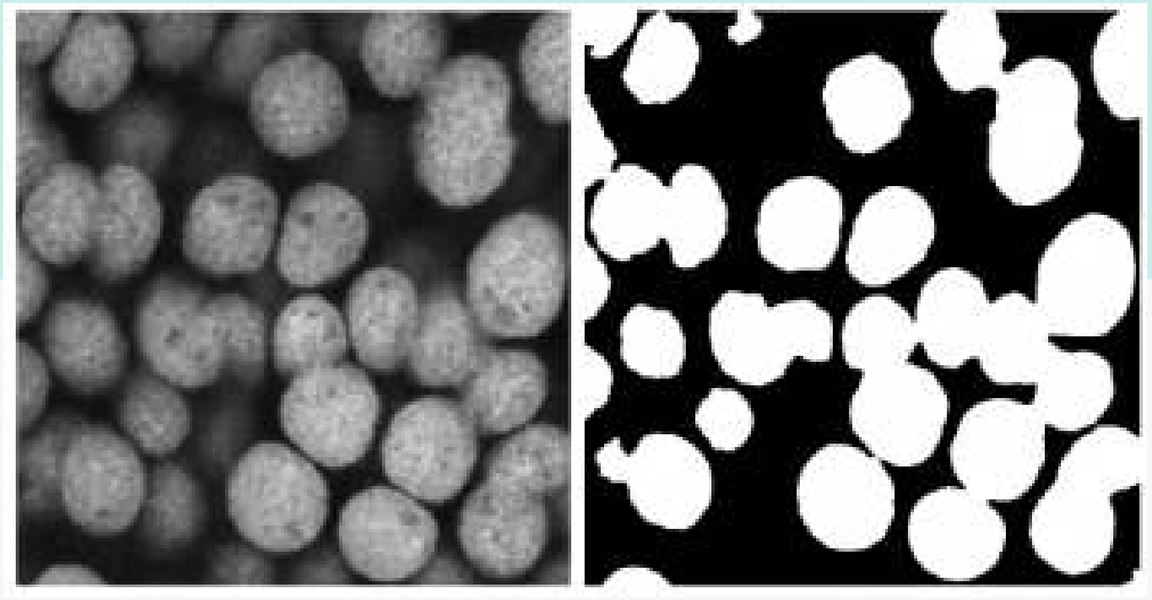
DJAHNINE AISSAM

INTRODUCTION

- MOTIVATION?
- WHY THIS PROJECT ?
- PROJECT OVERVIEW

SEGMENTATION , WHY ?



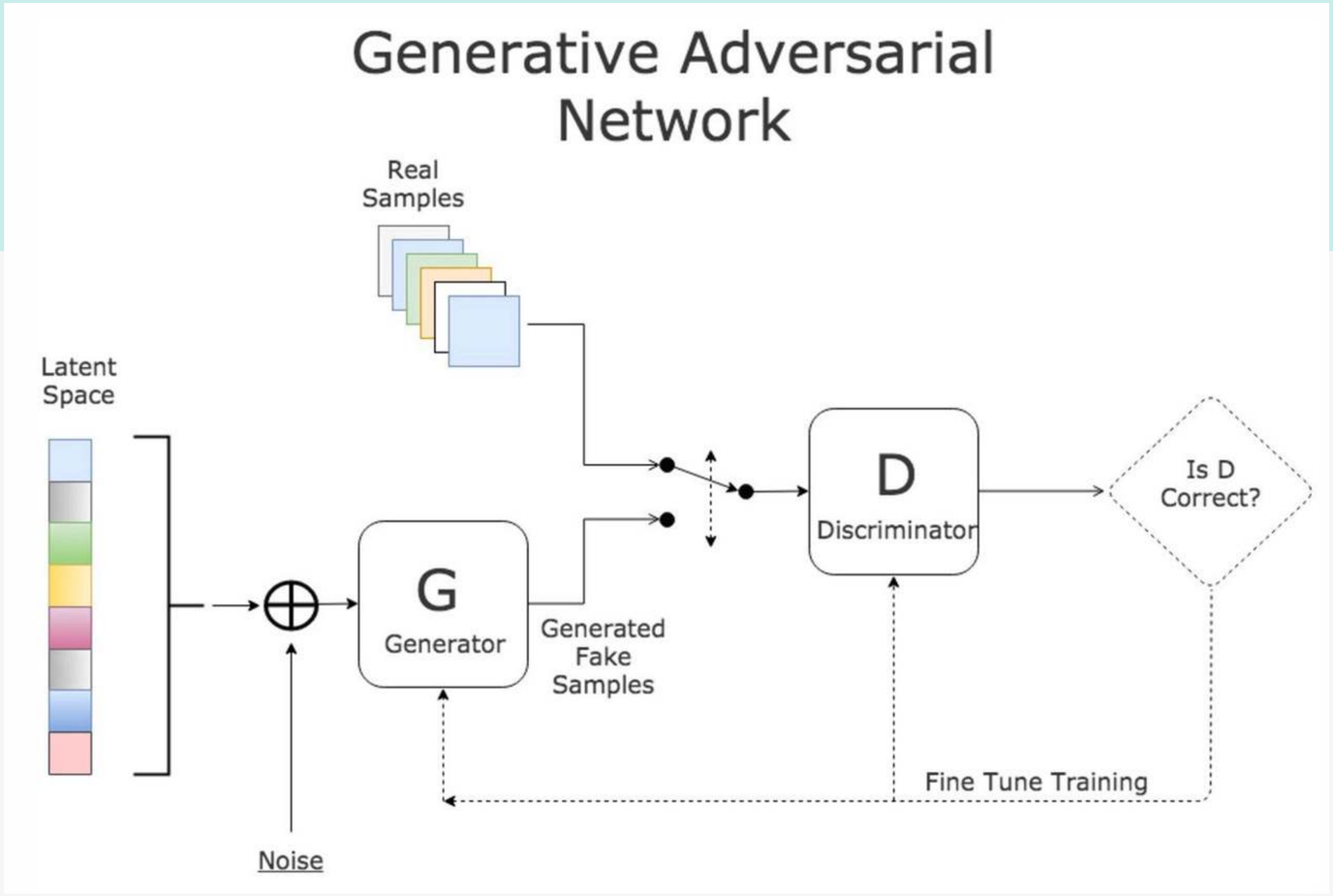


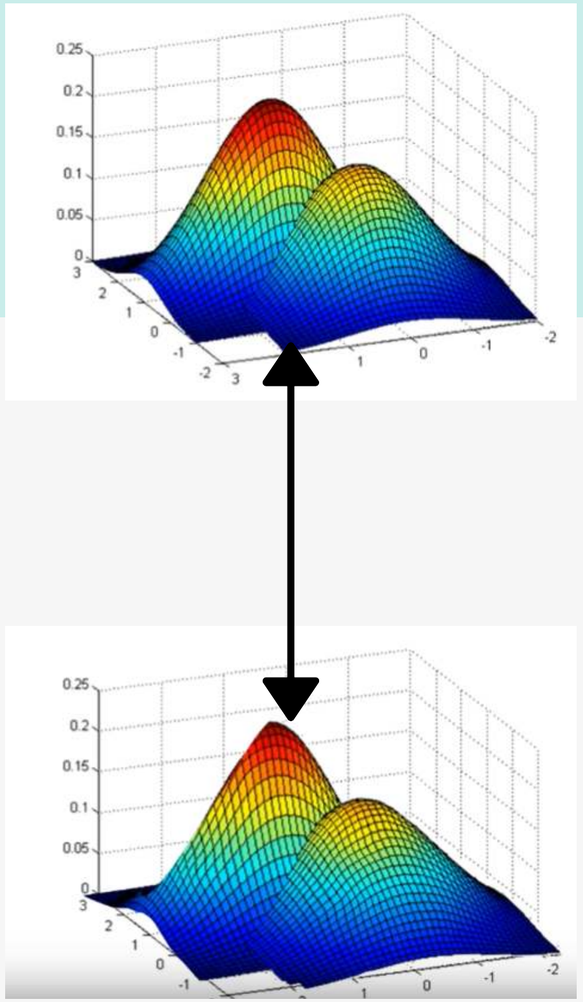
*MEDICAL IMAGE SEGMENTATION IS THE PROCESS OF AUTOMATIC OR SEMI-AUTOMATIC DETECTION OF BOUNDARIES WITHIN A 2D OR 3D IMAGE

PLAN

- GAN, CYCLE-GAN..HOW THEY WORK ?
    1. GENERATING IMAGES
    2. RESULTS
- APPROACHES (PAIRED,UNPAIRED..)
    1. PAIRED DATA
    2. UNPAIRED DATA
- MODELS ARCHITECTURE
    1. GENERATOR, DISCRIMINATOR
    2. TRAINING DETAILS
- DATASET
    1. GENERATOR, DISCRIMINATOR
    2. TRAINING DETAILS
- RESULTS AND COMMENTS
    1. LOSS PLOTS
    2. SEGMENTATION RESULT
    3. METRICS

WHAT'S GAN ?

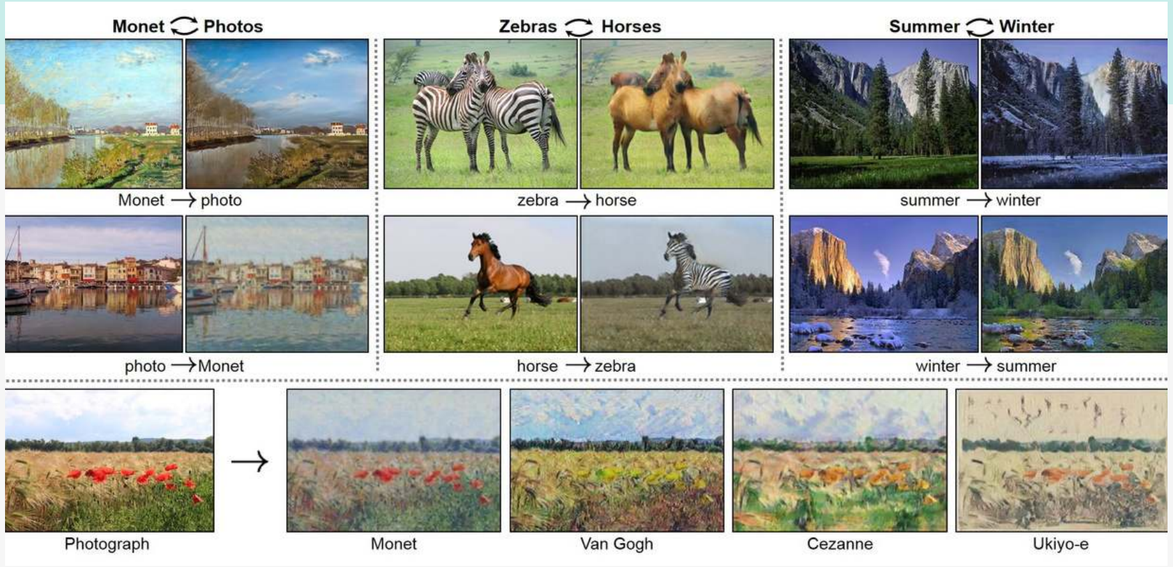

Generative Adversarial Network
Real Samples
Latent Space
G
Generator
Generated Fake Samples
D
Discriminator
Is D Correct?
Fine Tune Training
Noise



CYCLE-GAN

Cycle-Consistent Generative Adversarial Networks

- IMAGE-TO-IMAGE TRANSLATION PROBLEM



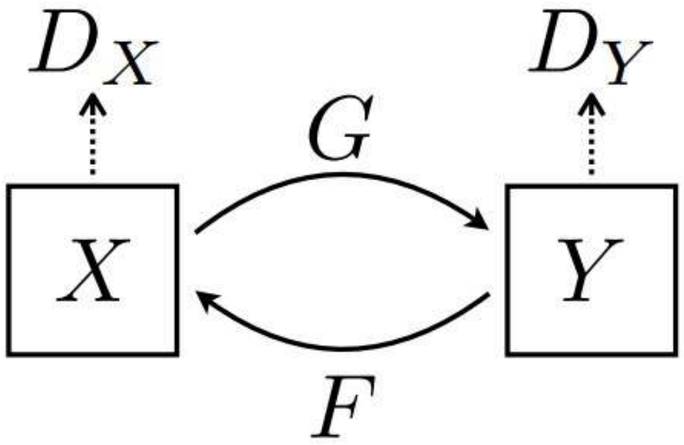
Source : Paper Cycle-Consistent Generative Adversarial Networks

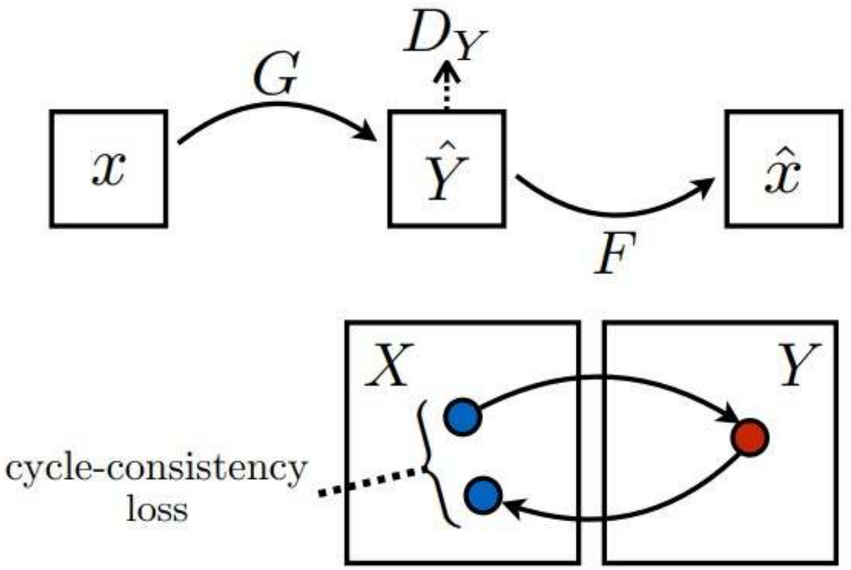


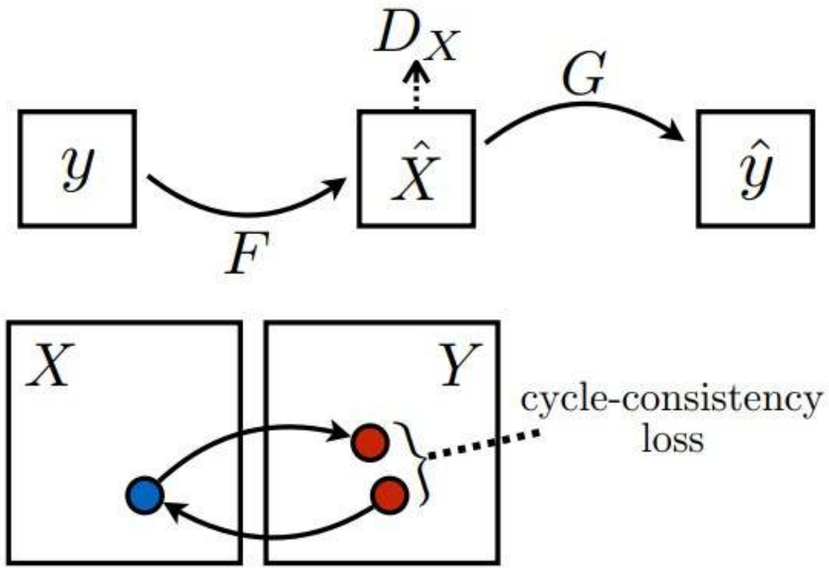
- MAPPING BETWEEN AN INPUT IMAGE AND AN OUTPUT IMAGE

CYCLE-GAN

Cycle-Consistent Generative Adversarial Networks







ADVERSARIAL LOSSES

$$\mathcal{L}_{GAN}(G, D_Y, X, Y) = \mathbb{E}_{y \sim pdata(y)}[log\, D_Y(y)] + \mathbb{E}_{x \sim pdata(x)}[log(1 - D_Y(G(x))]$$

$$\mathcal{L}_{GAN}(F, D_X, Y, X) = \mathbb{E}_{x \sim pdata(x)}[log\, D_X(x)] + \mathbb{E}_{y \sim pdata(y)}[log(1 - D_X(F(y))]$$

$$min_G\, max_{D_Y}\, \mathcal{L}_{GAN}(G, D_Y, X, Y)$$

$$min_F\, max_{D_X}\, \mathcal{L}_{GAN}(F, D_X, Y, X)$$

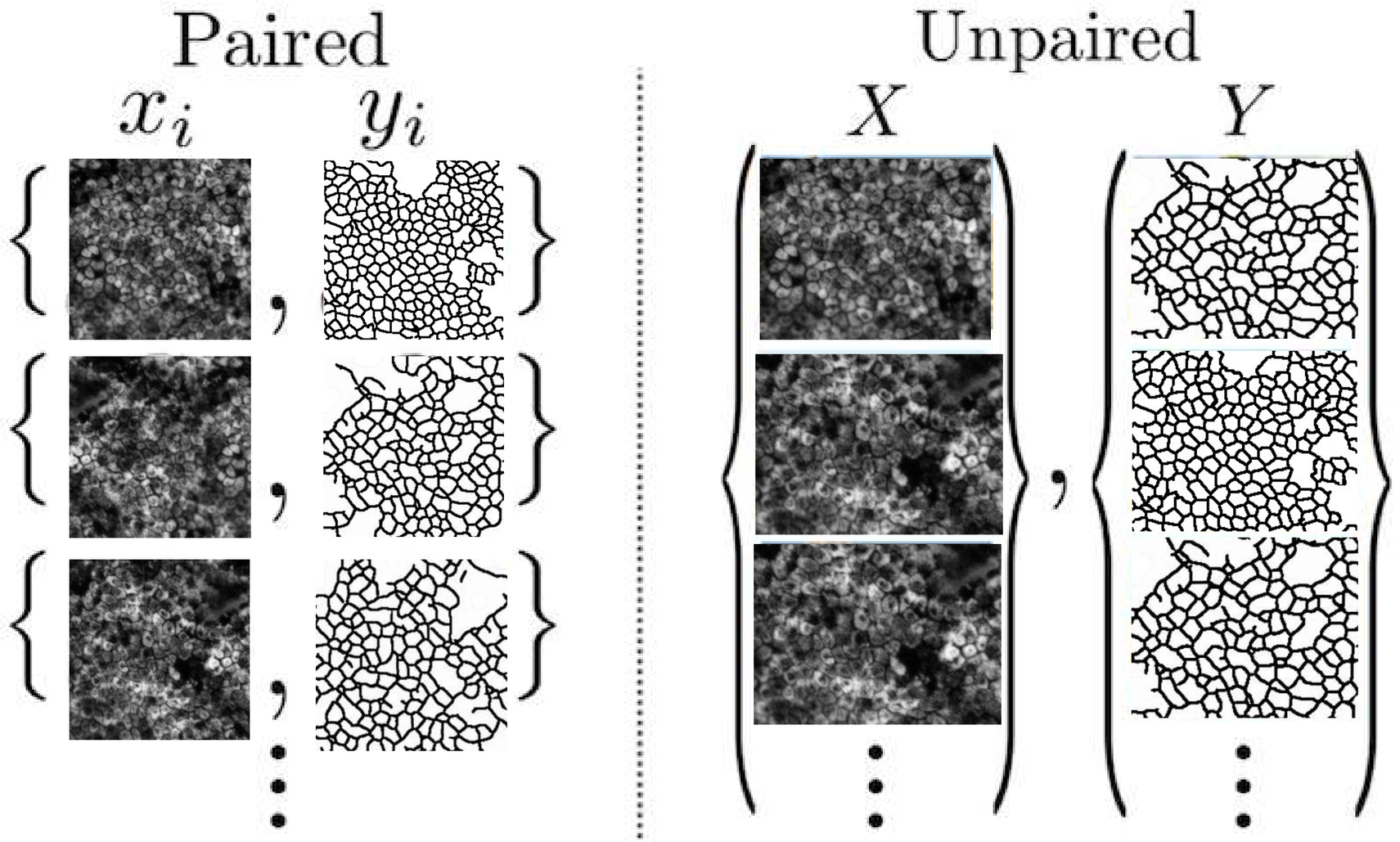
CYCLE-CONSISTENCY LOSS

$$\mathcal{L}_{cycle}(G, F) = \mathbb{E}_{x \sim pdata(x)}[\| F(G(x)) - x \|_1] + \mathbb{E}_{y \sim pdata(y)}[\| G(F(y)) - y \|_1]$$

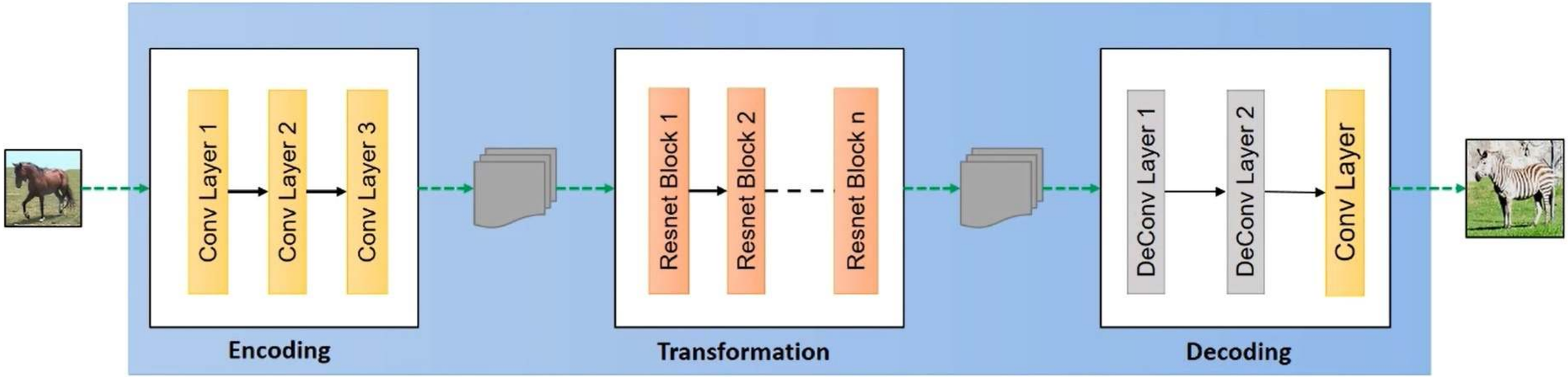
FULL OBJECTIVE

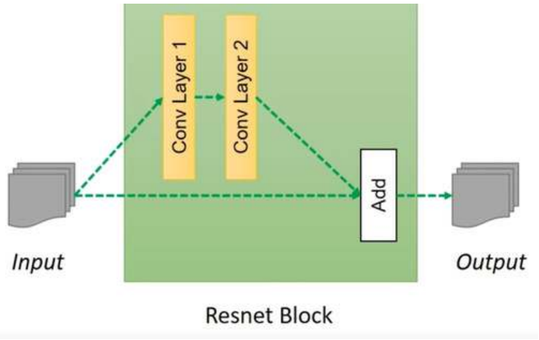
$$\mathcal{L}(G, F, D_X, D_Y) = \mathcal{L}_{GAN}(G, D_Y, X, Y) + \mathcal{L}_{GAN}(F, D_X, Y, X) + \lambda \mathcal{L}_{cycle}(G, F)$$

PAIRED VS UNPAIRED APPROACH



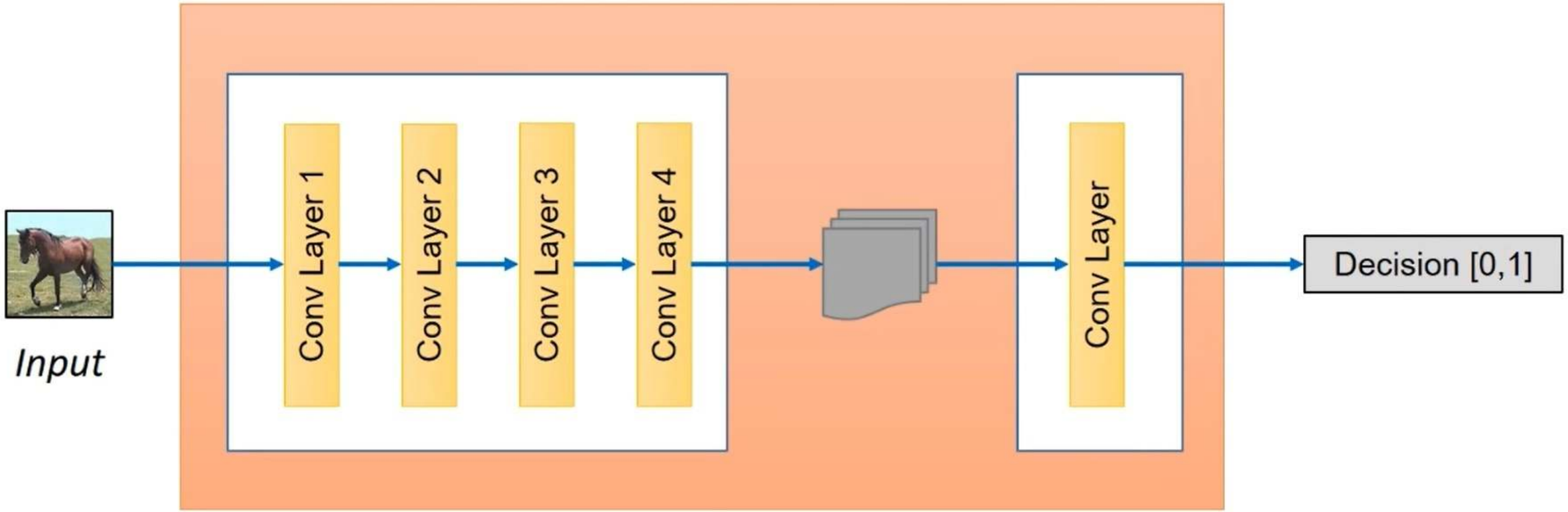
GENRATOR





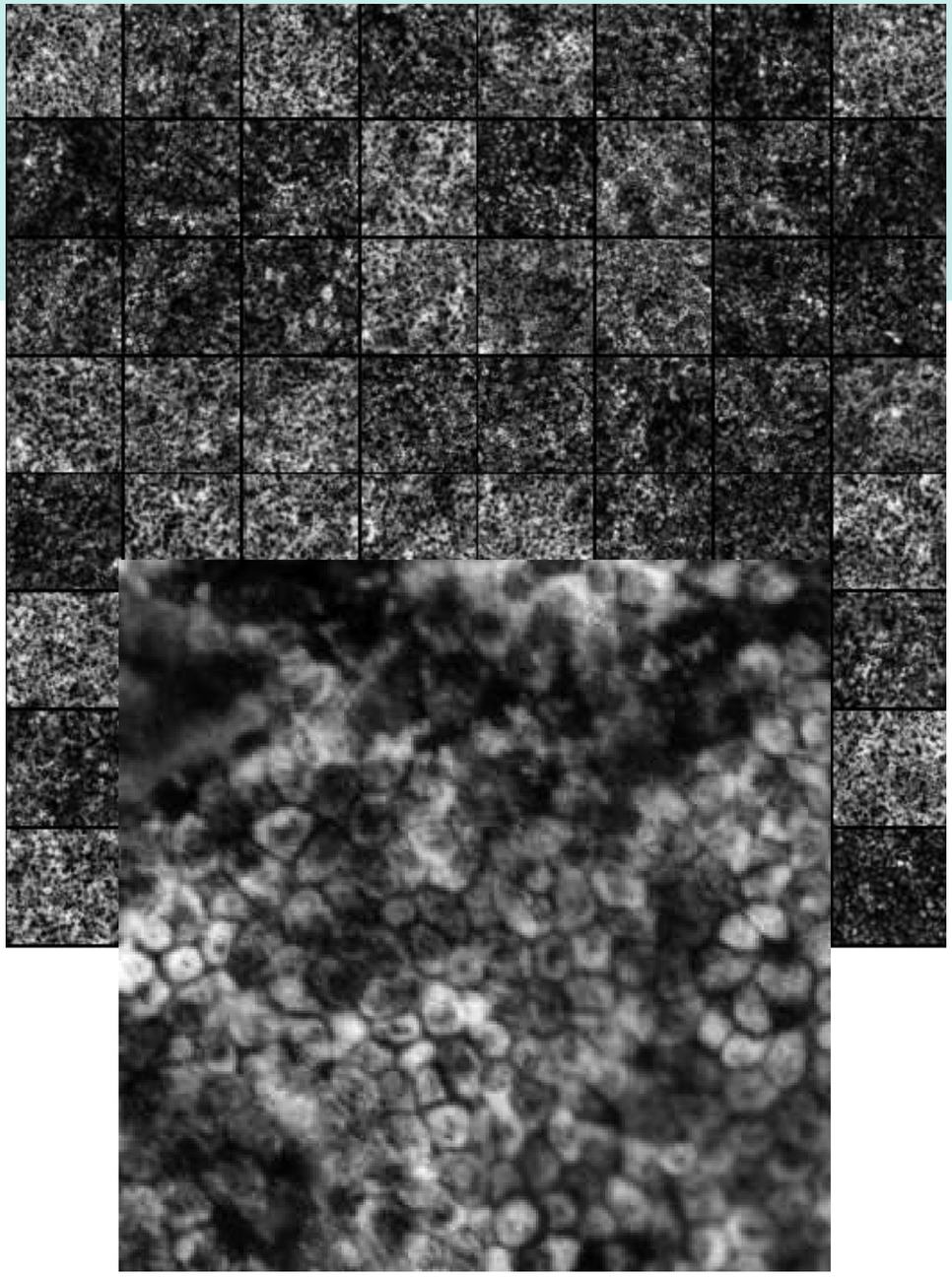
Source : Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks paper

DISCRIMINATOR



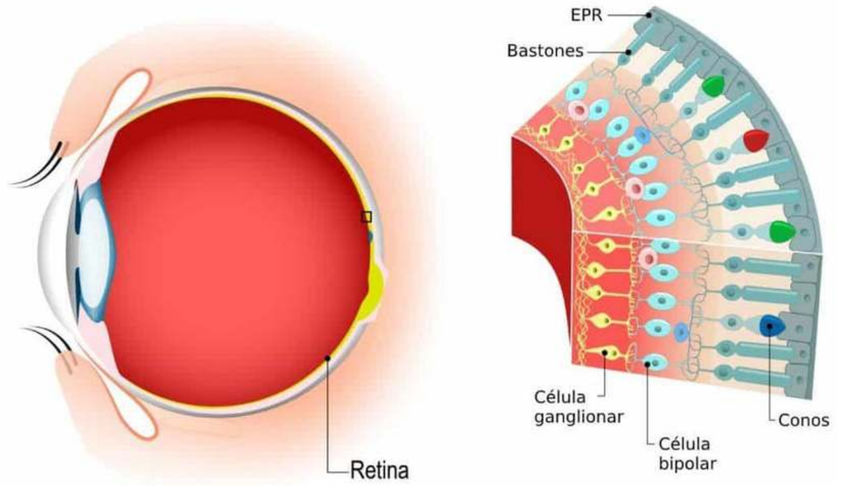
Source : Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks paper

DATASET



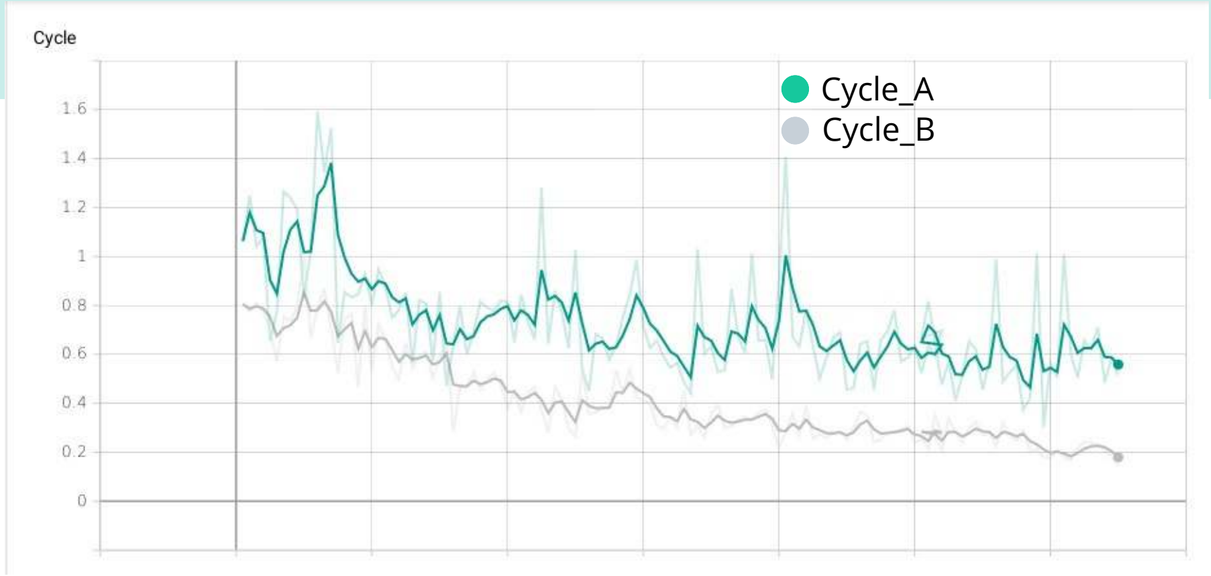
Source : National Institute of Standards and Technology

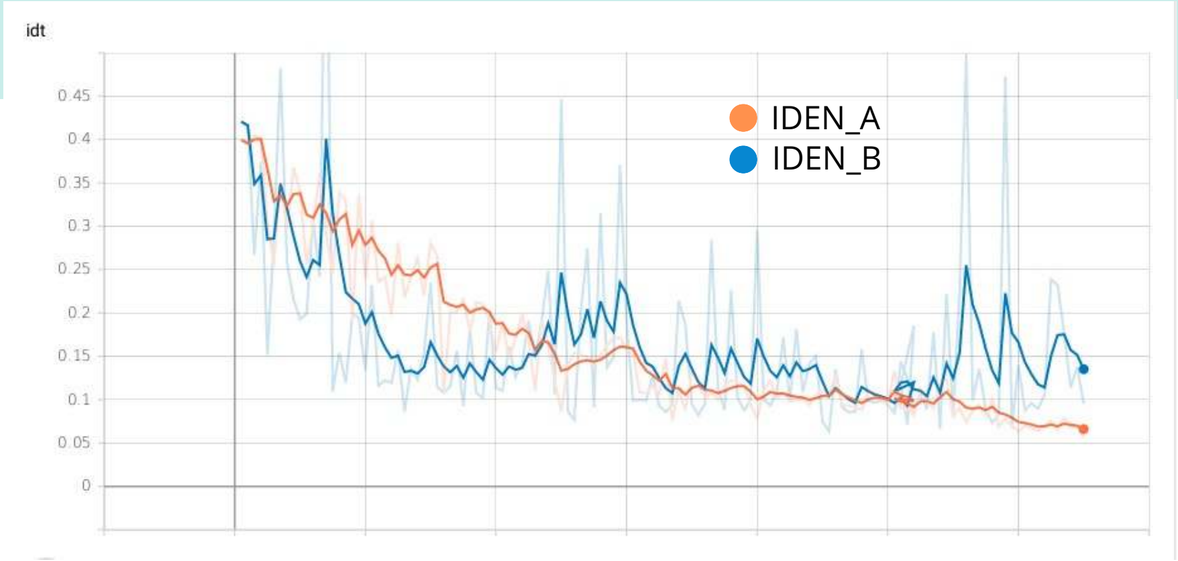
1032 256x256 absorbnce microscopy images of human retinal Pigment Epithelium

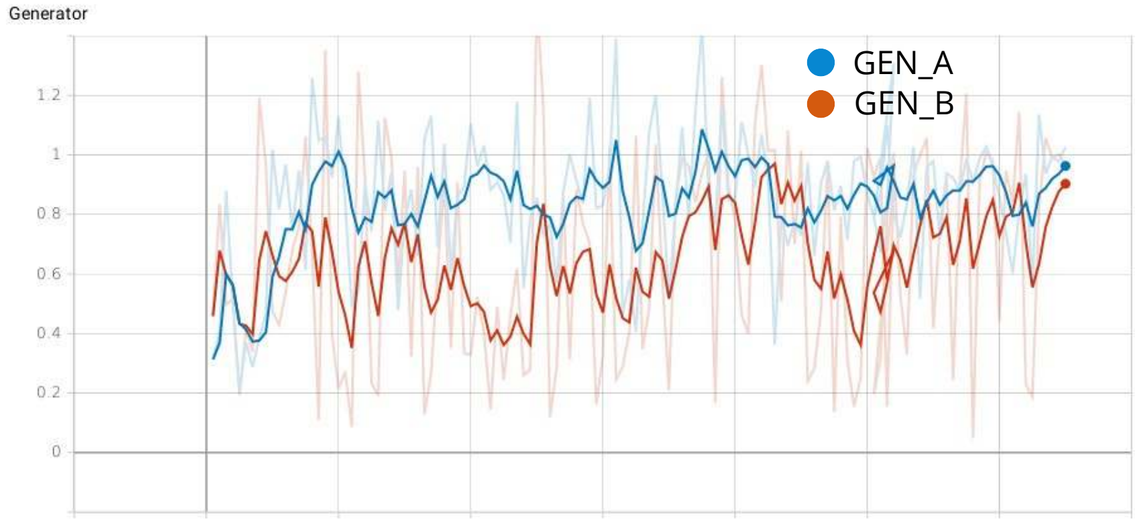


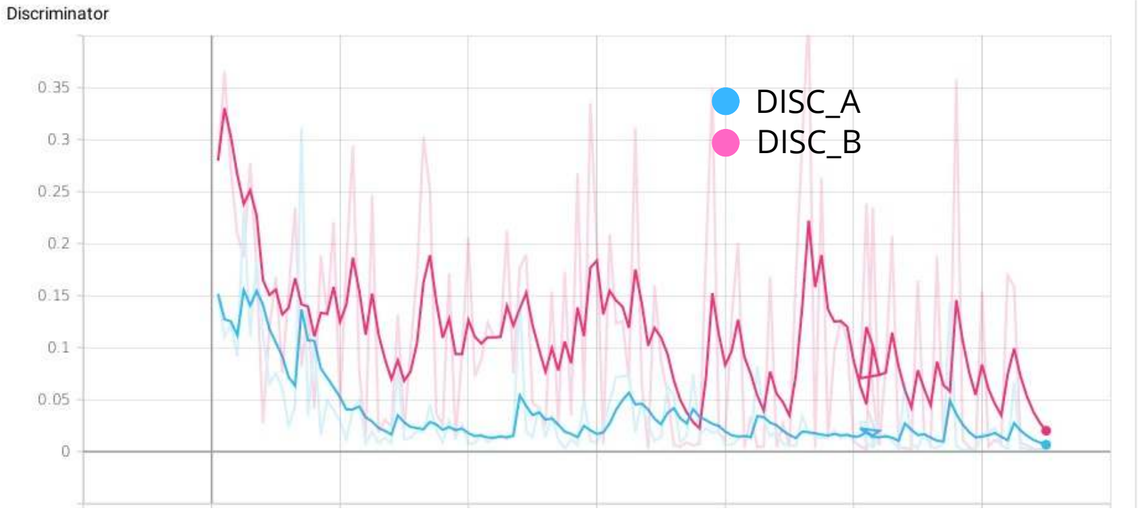
Source : areaoftalmologica.com

RESULTS

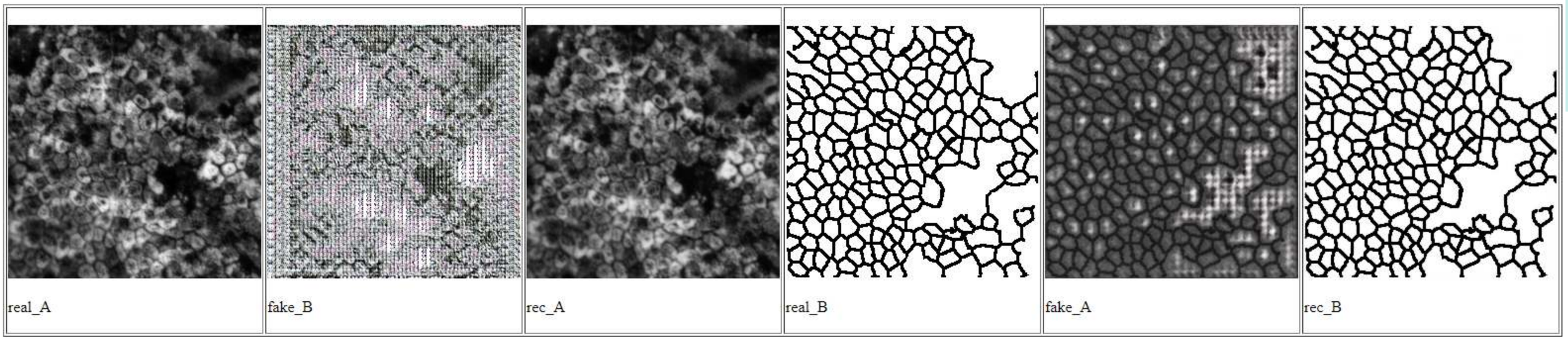

Cycle
Cycle_A
Cycle_B
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0


idt
IDEN_A
IDEN_B
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0

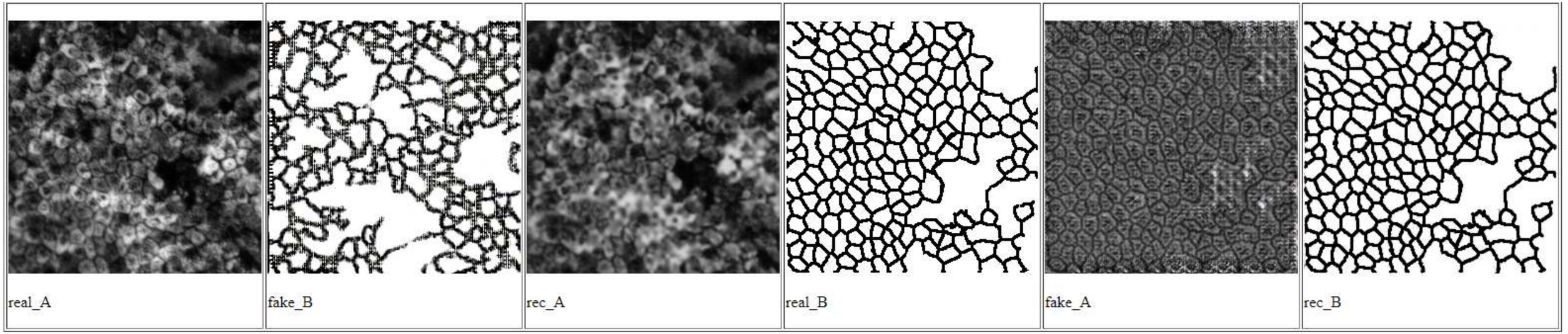

Generator
GEN_A
GEN_B
1.2
1
0.8
0.6
0.4
0.2
0


Discriminator
DISC_A
DISC_B
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0

RESULTS

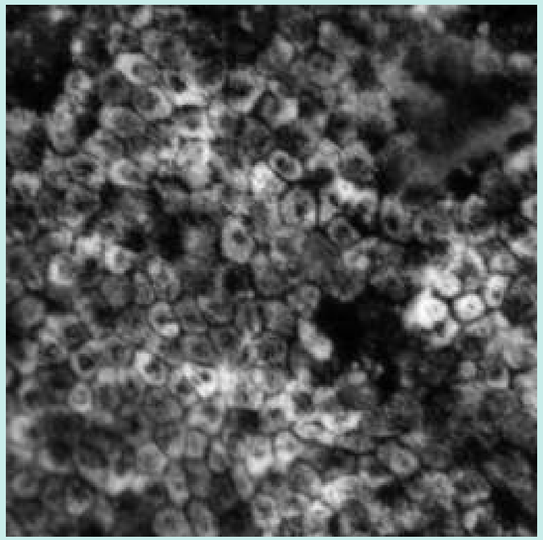


EPOCH: 10

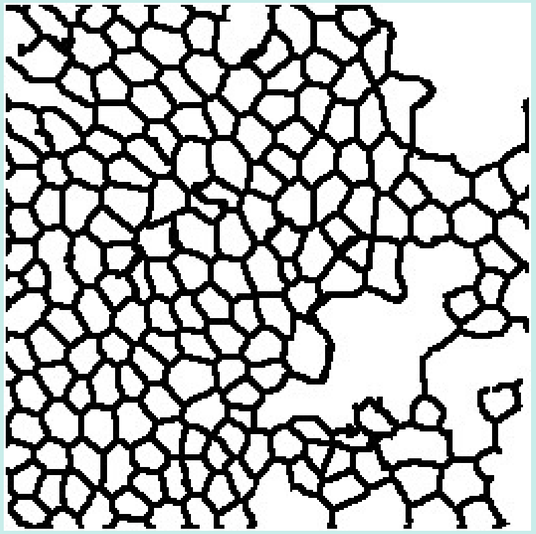


EPOCH: 90

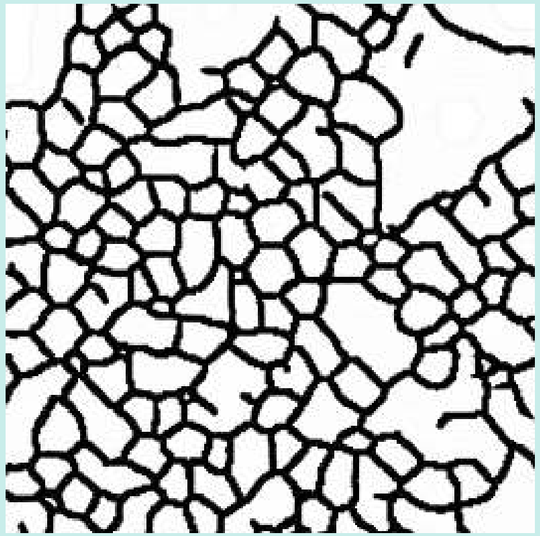
RESULTS AND METRICS



Input



Ground Truth



Cycle_gan

9.5082

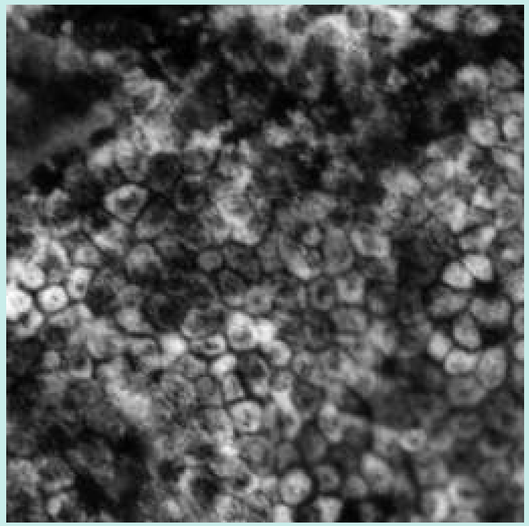
Hausdorff Distance

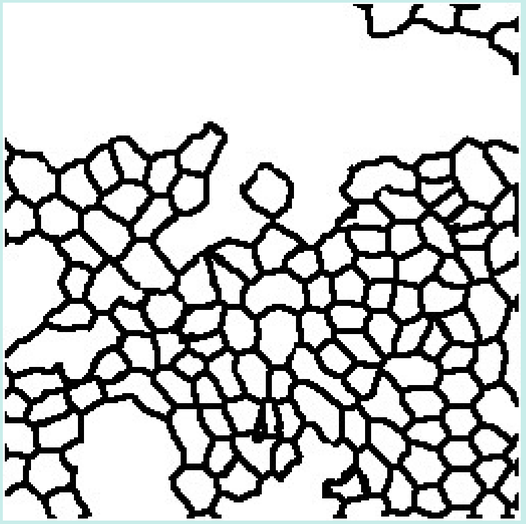
0.398

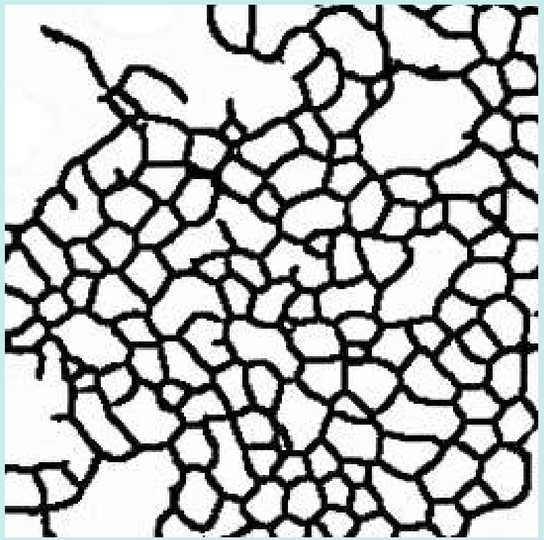
Perceptual Similarity

0.85066

Dice Similarity Coefficient







9.4055

Hausdorff Distance

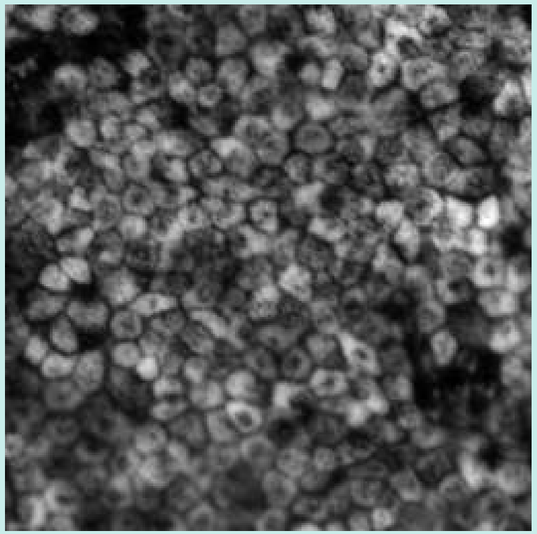
0.324

Perceptual Similarity

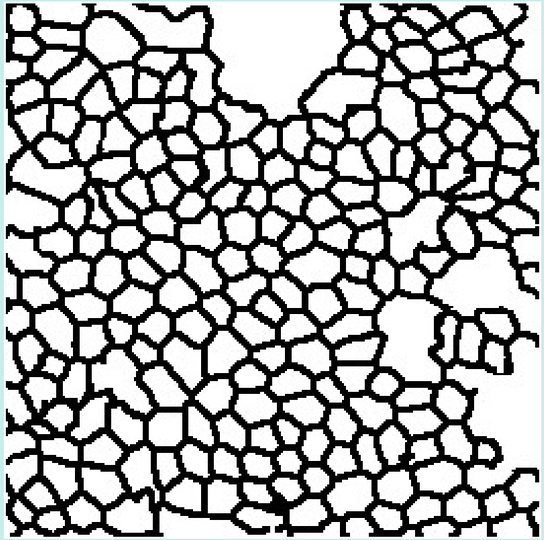
0.86987

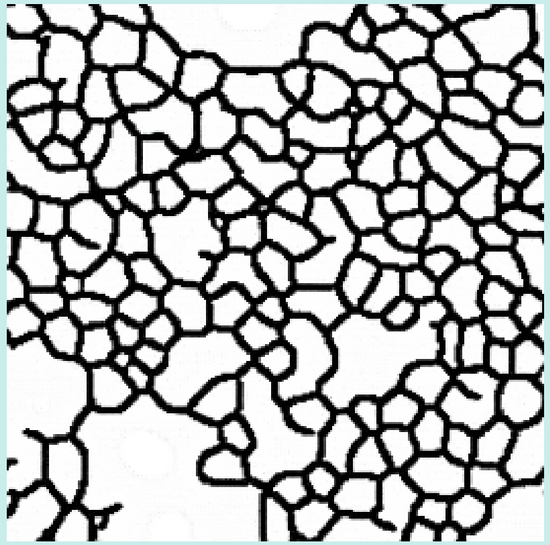
Dice Similarity Coefficient

RESULTS AND METRICS



Ground Truth





cycle_gan segmentation

9.7022

Hausdorff Distance

0.453

Perceptual Similarity

0.7897

Dice Similarity Coefficient

CONCLUSION

WE CAN TREAT REAL WORLD PROBELMS WHERE PAIRED DATA IS NOT AVAILABLE WITH CYLCE-GANS

TRAINING A GAN IS NOT EASY, AND THE EQUILIBRIUM POINT IS RARELY REACHED

ANOTHER LOSS FUNCTIONS CAN BE USED TO BUILD BETTER MODELS (IDENTITY LOSS..)

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S. Kazeminia, C. Baur, A. Kuijper, B. van Ginneken, N. Navab, S. Albarqouni, and A. Mukhopadhyay, “GANs for medical image analysis.” [Online]. Available: http://arxiv.org/abs/1809.06222

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