Exploring the impact of Transfer Learning and Semi Supervised GANs for Tumor Classification In Medical Imaging

FYP RESEARCH PROJECT DEFENSE

SUPERVISOR: DR. M. IRFAN UDDIN

S.No.	Student Name	GPA
S1	Hussam Umer	3.75
S2	NIL	N/A
S3	NIL	N/A

Table of Contents

Research Title

Exploring the impact of Transfer Learning and Semi Supervised GAN for Tumor Classification

Research Questions

- How does transfer learning impact the performance of CycleGAN in generating synthetic medical images for tumor classification?
- What are the computational requirements and training time differences between TL-SCycleGAN and traditional CycleGAN for generating synthetic medical images?
- Can TL-SCycleGAN effectively overcome domain shift issues when applied to different medical imaging modalities for tumor classification?
- How does the performance of TL-SCycleGAN compare with other state-of-the-art methods for synthetic data generation in medical imaging?

Problem Statement

In recent research,

- Identification of benign and malignant tumors in medical imaging is challenging
- Existing deep learning approaches require large labeled datasets for effective training
- Imbalance between benign and malignant cases further complicates classification
- Data diversity and realism, which means generating diverse and realistic synthetic tumor images

Base Research Papers

Title	Author	Date	Model
Transfer Learning-Based Semi-Supervised Generative Adversarial Network for Malaria Classification	*Ibrar Amin , Saima Hassan , Samir Brahim Belhaouari, and Muhammad Hamza Azam*	2022	TL-S-GAN
Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks	*Jun-Yan Zhu, Taesung Park, Phillip Isola, Alexie A.Afros*	*2017*	Cycle-GAN
Deep Residual Learning for Image Recognition	*Kaiming He; Xiangyu Zhang; Shaoqing Ren; Jian Sun*	2016	ResNET-50
Very deep convolutional networks for large-scale image recognition	*Karen Simonyan & Andrew Zisserman*	2015	VGG-16

Background

Cycle GAN is a Generative Adversarial Network (GAN) that uses *two* generators and *two* discriminators.

One generator *G*, it convert images from the *X* domain to the *Y* domain. The other generator is called *F*, and converts images from *Y* to *X*.

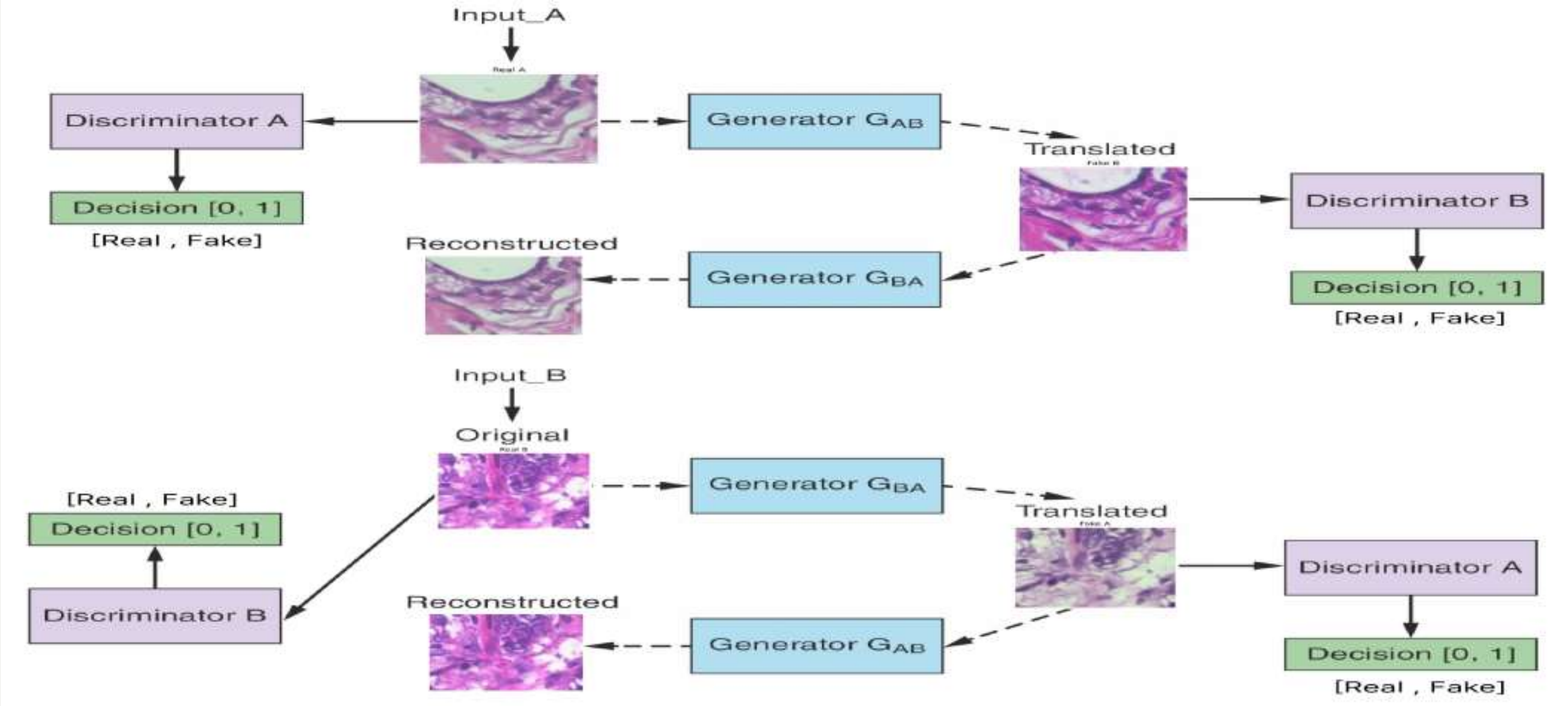
$$G : X \rightarrow Y$$
$$F : Y \rightarrow X$$

Each generator has a corresponding discriminator, which attempts to tell apart its synthesized images from real ones.

D_y : Distinguishes y from G(x)

D_x : Distinguishes x from F(y)

Working Flow(Cycle GAN)



Architecture

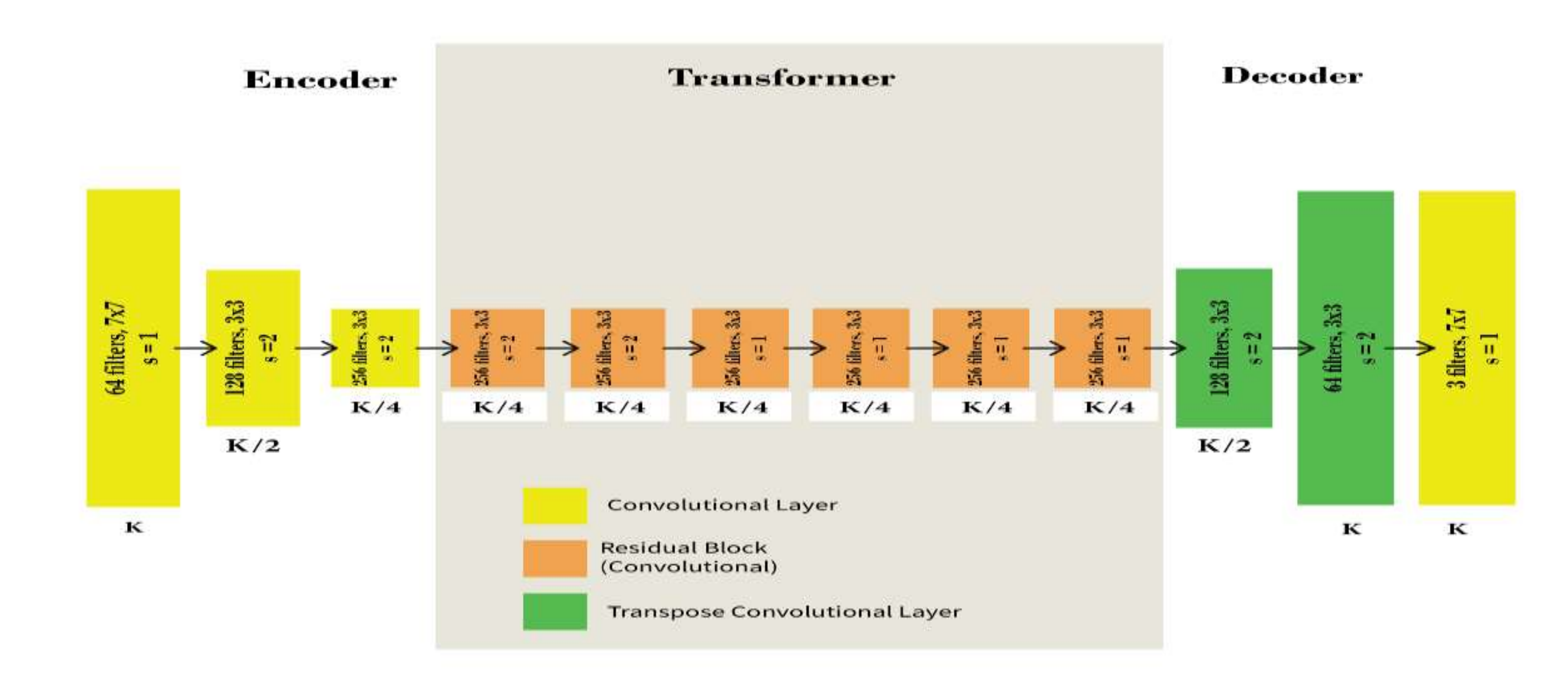
Generator Architecture:

- Encoder
- Transformation Blocks
- Decoder

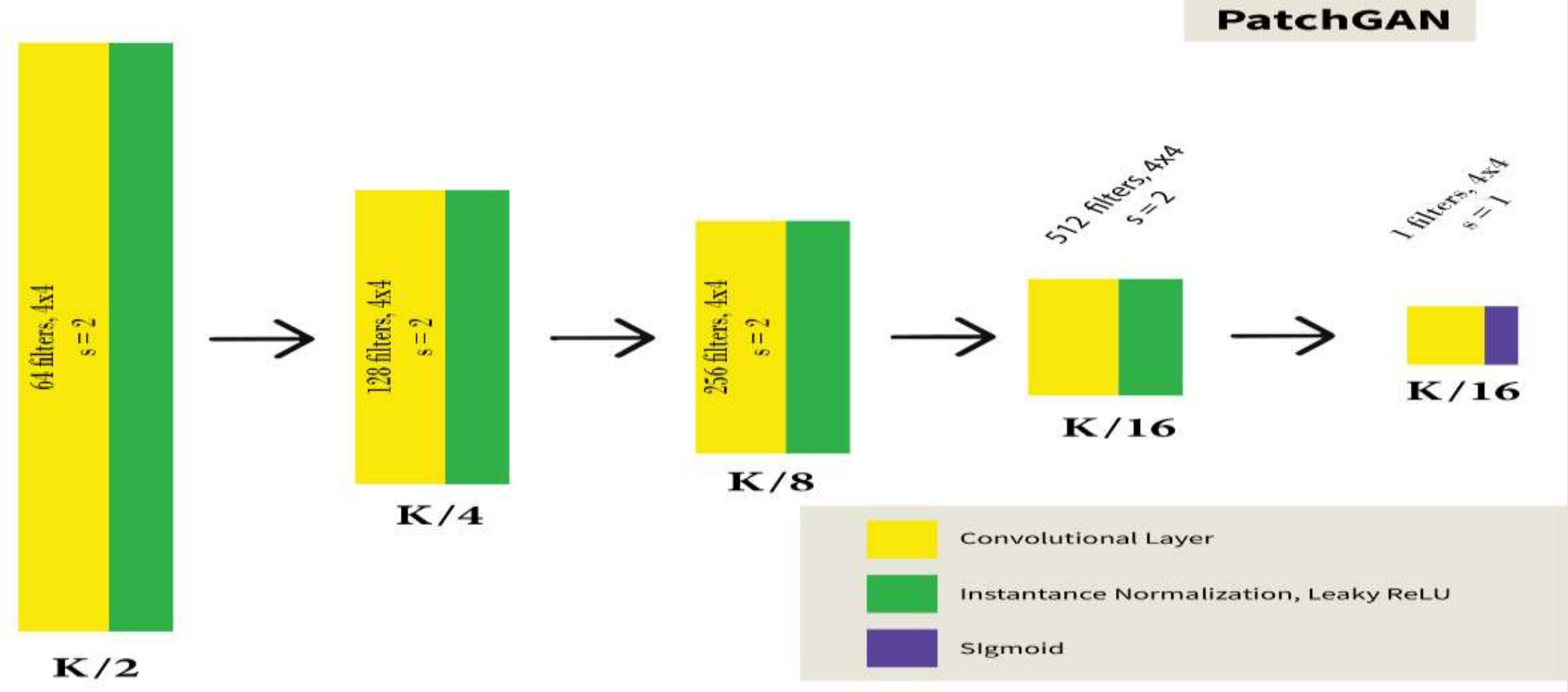
Discriminator Architecture:

- PatchGAN

Architecture(Generator)



Architecture(Discriminator)

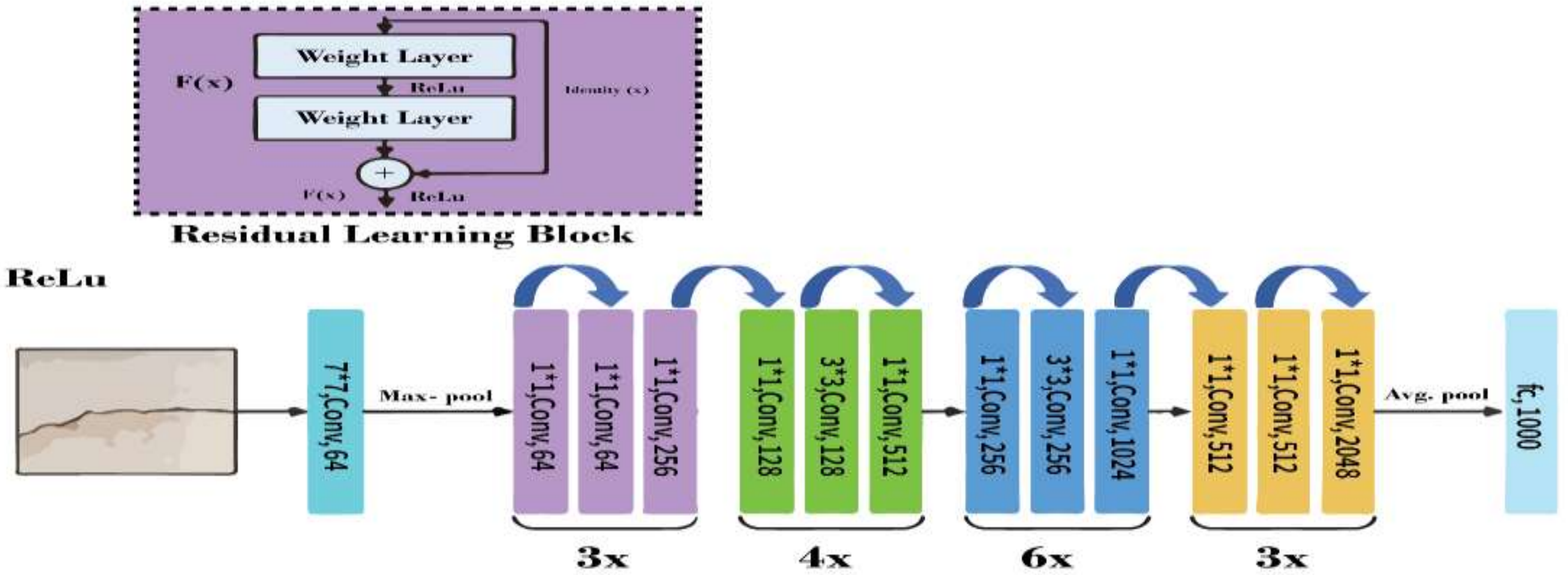


The Proposed Architecture

1. ResNET-50:

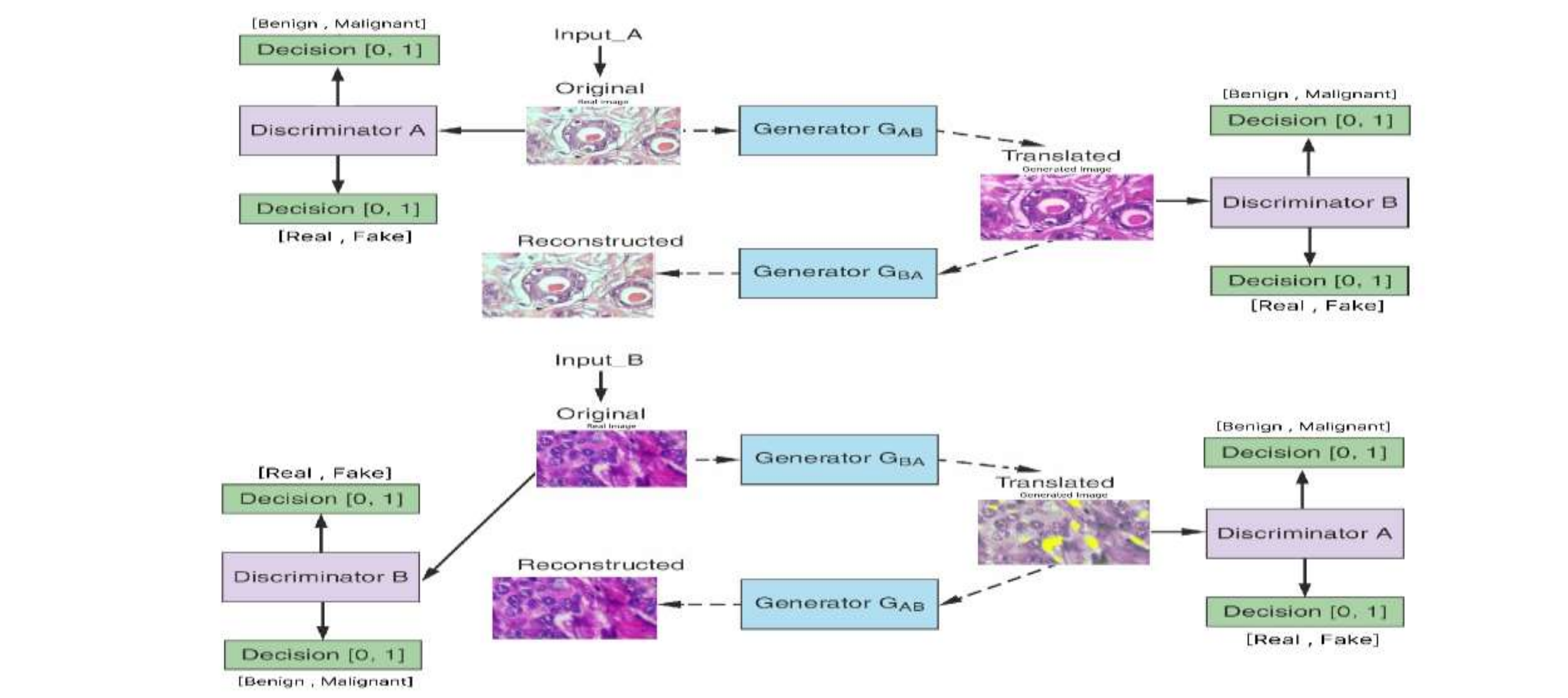
- Initial Layer
- Pooling Layer
- Residual Block
- Bottleneck Design
- Block Stacking
- Avg. Pooling Layer
- Fully connected Layer

ResNET-50



Weight Layer
F(x)
ReLu
Identity (x)
Weight Layer
F(x)
ReLu
Residual Learning Block
ReLu
7*7,Conv,64
Max- pool
1*1,Conv,64
1*1,Conv,64
1*1,Conv,256
1*1,Conv,128
3*3,Conv,128
1*1,Conv,512
1*1,Conv,256
3*3,Conv,256
1*1,Conv,1024
1*1,Conv,512
1*1,Conv,512
1*1,Conv,2048
Avg. pool
fc,1000
3x
4x
6x
3x

Working Flow(ResNET- 50 Cycle GAN)

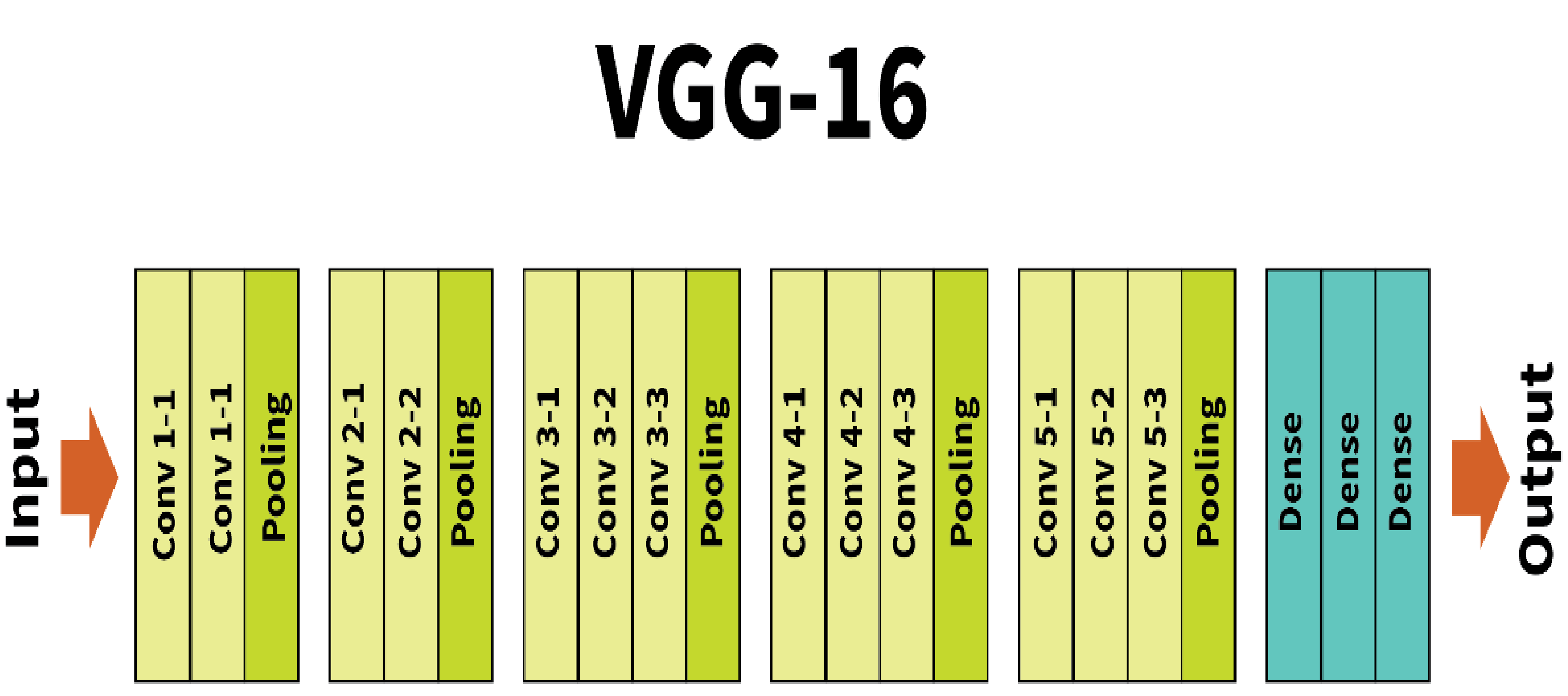


The Proposed Architecture

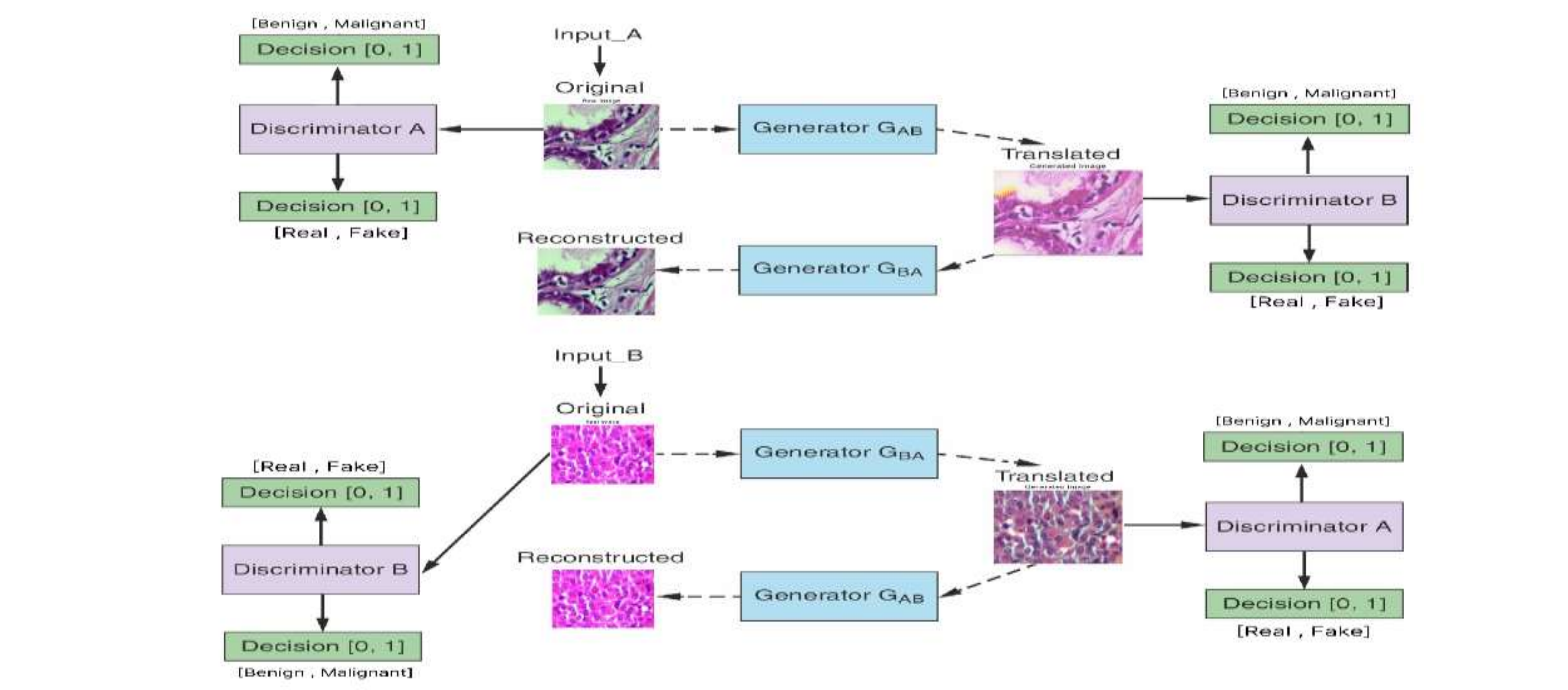
2. VGG-16:

- Convolutional Layers
- Pooling Layer
- Fully Connected Layers
- Block Structure
- Architecture Depth
- Design Philosophy

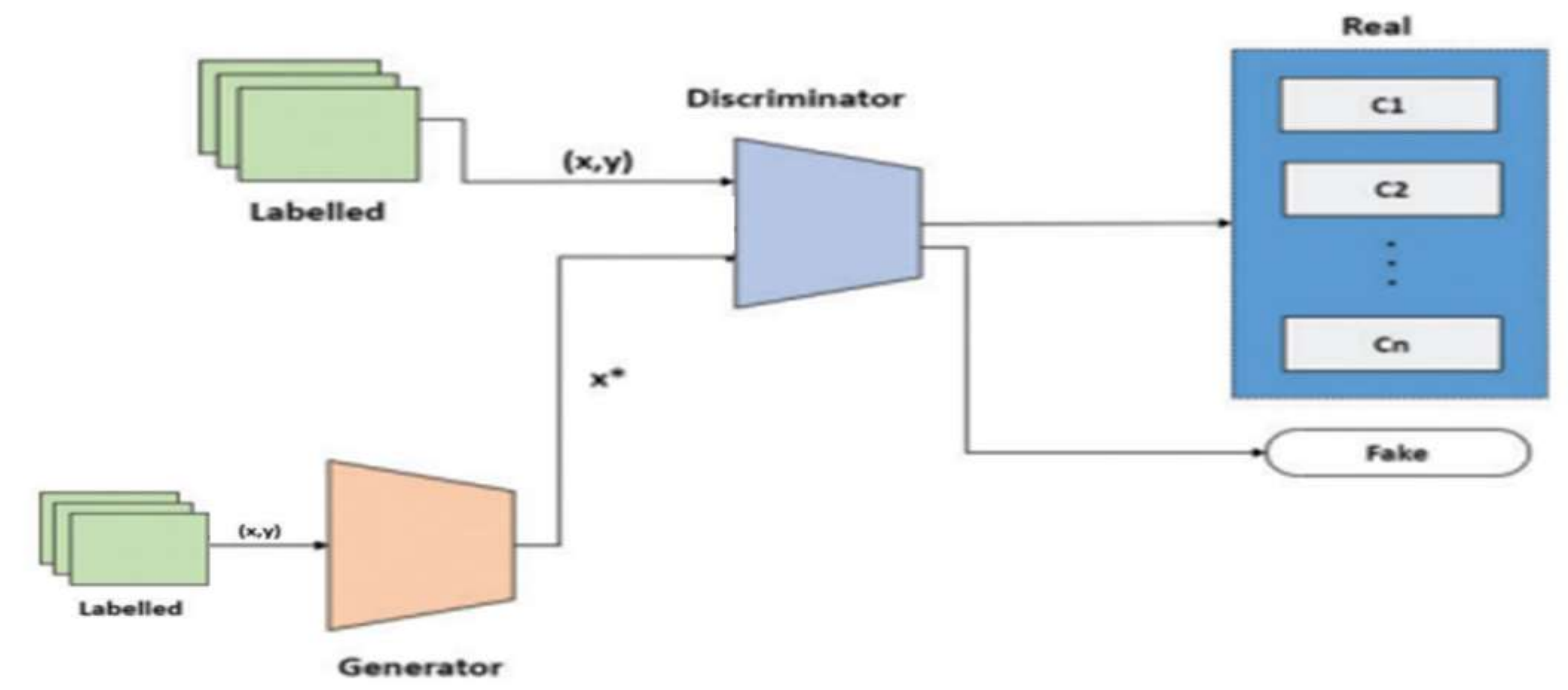
VGG-16


VGG-16
Input
Conv 1-1
Conv 1-1
Pooling
Conv 2-1
Conv 2-2
Pooling
Conv 3-1
Conv 3-2
Conv 3-3
Pooling
Conv 4-1
Conv 4-2
Conv 4-3
Pooling
Conv 5-1
Conv 5-2
Conv 5-3
Pooling
Dense
Dense
Dense
Output

Working Flow(VGG-16 Cycle GAN)



Semi-Supervision



The objective Function

There are two components to the CycleGAN objective function, an *adversarial loss* and a *cycle consistency loss*. Both are essential to getting good results.

1. Adversarial Loss :

The adversarial loss measures how well the generator can fool the discriminator.

The objective is to minimize this loss, which encourages the generator to generate realistic data samples.

$$Loss_{adv}(G, D_y, X) = \frac{1}{m}\sum_{i=1}^{m}(1 - D_y(G(x_i)))^2$$

$$Loss_{adv}(F, D_x, Y) = \frac{1}{m}\sum_{i=1}^{m}(1 - D_x(F(y_i)))^2$$

The objective Function(Cont.)

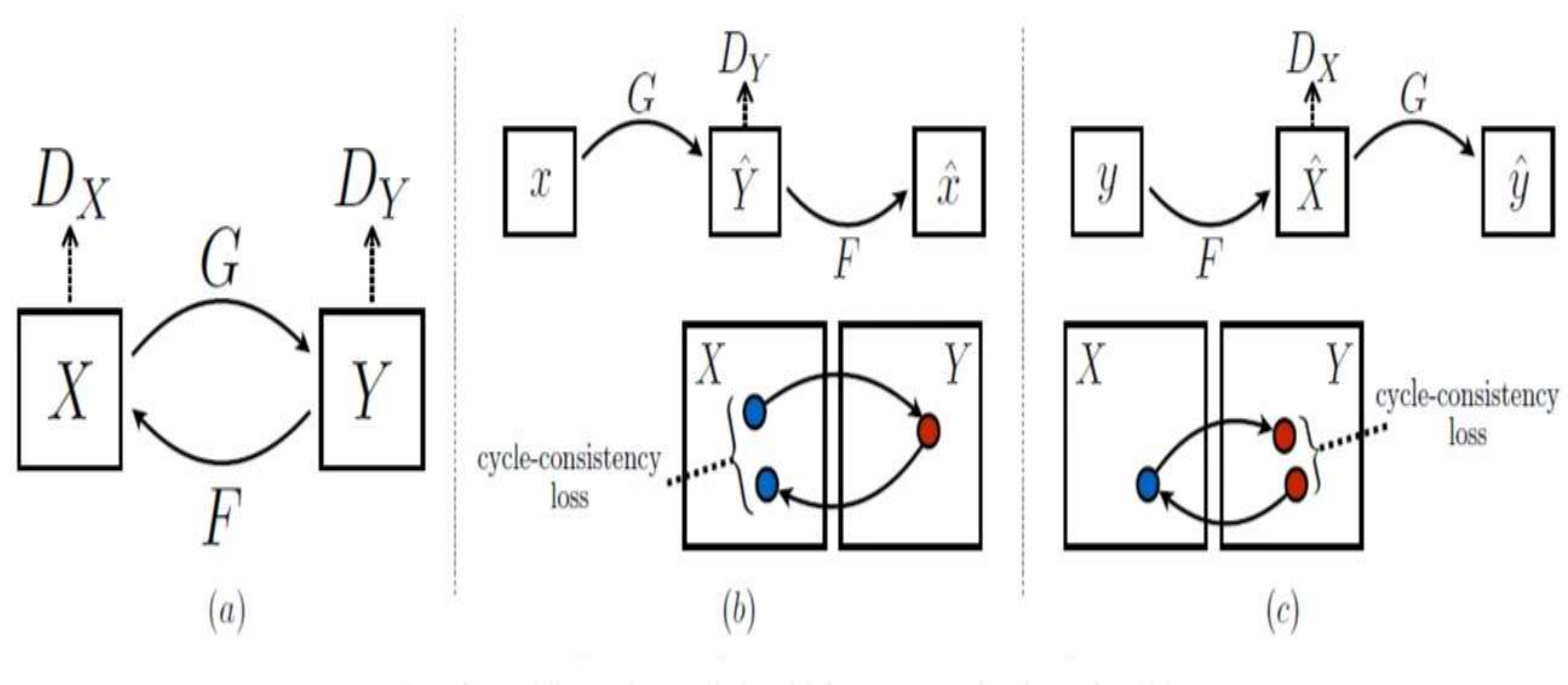
2. Cycle-Consistency Loss:

The cycle-consistency loss is introduced to enforce that the output generated by the generator, when passed through another generator in the opposite direction, should reconstruct the original input.

It enforces that $F(G(x)) \approx x$ and $G(F(y)) \approx y$.

$$Loss_{cyc}(G, F, X, Y) = \frac{1}{m}\sum_{i=1}^{m}[F(G(x_i)) - x_i] + [G(F(y_i)) - y_i]$$

The objective Function(Cont.)



The objective Function(Cont.)

3. Cross Entropy Loss:

The cross entropy loss quantifies the difference between the predicted probability distribution and the actual distribution.

For binary classification, it is defined as:

$$\mathcal{L} = -\left[y\log(p) + (1-y)\log(1-p)\right]$$

Where:

- y is the actual label (0 or 1).
- p is the predicted probability of the positive class (1).

Dataset

BreakHis Histology Slides

Total Images = 210

Training = 200

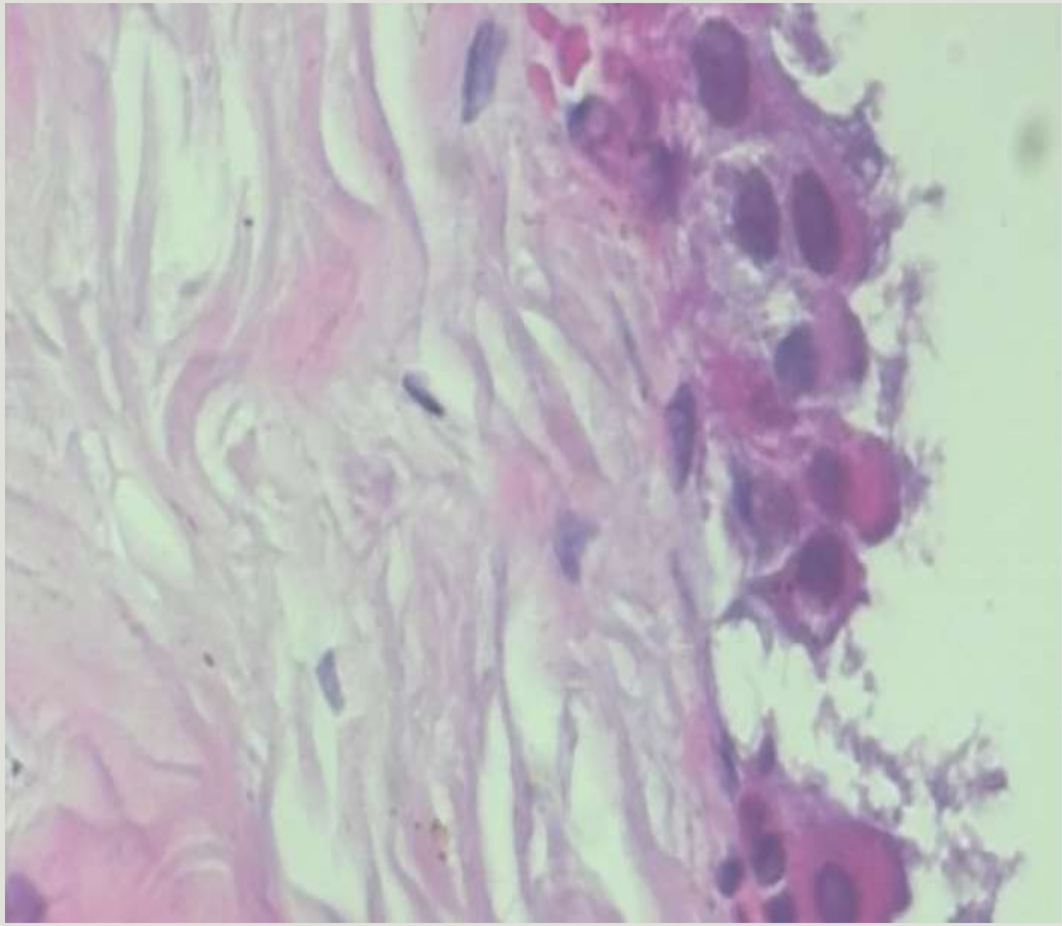
- Benign = 100
- Malignant = 100

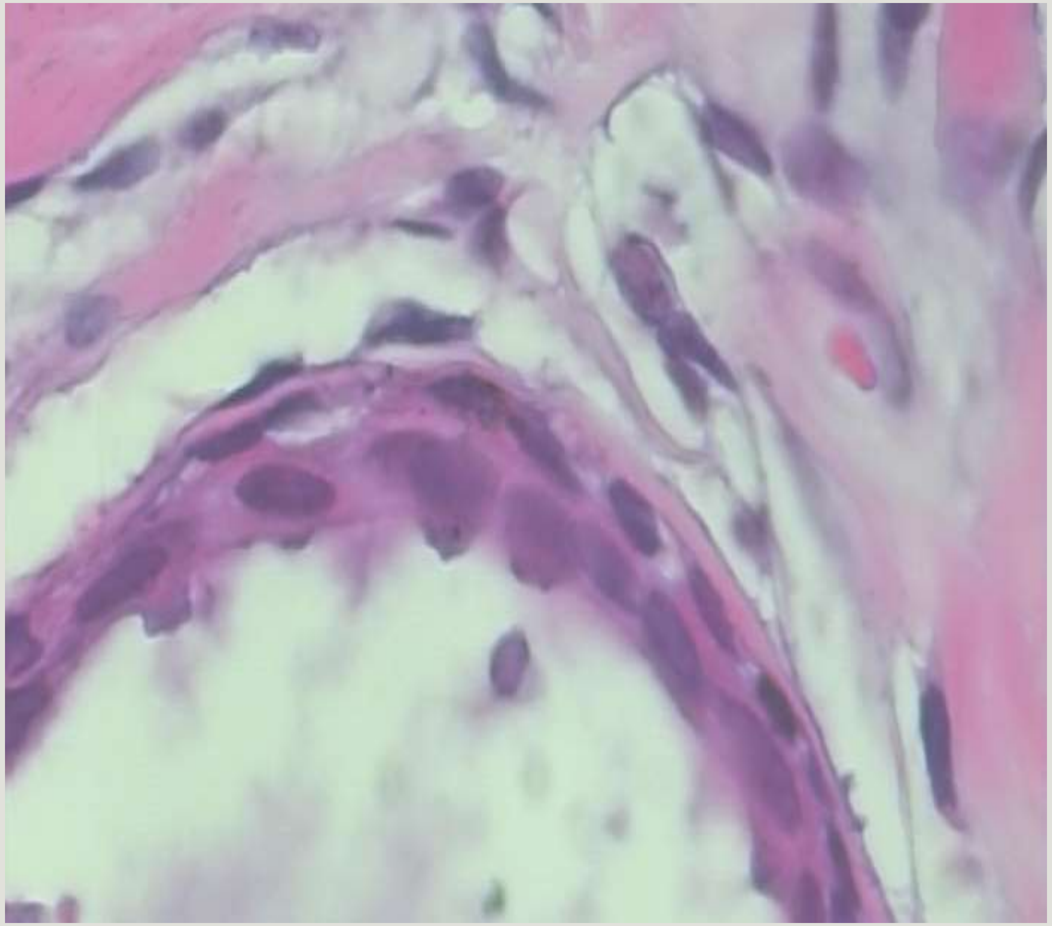
Testing = 20

- Benign = 10
- Malignant = 10

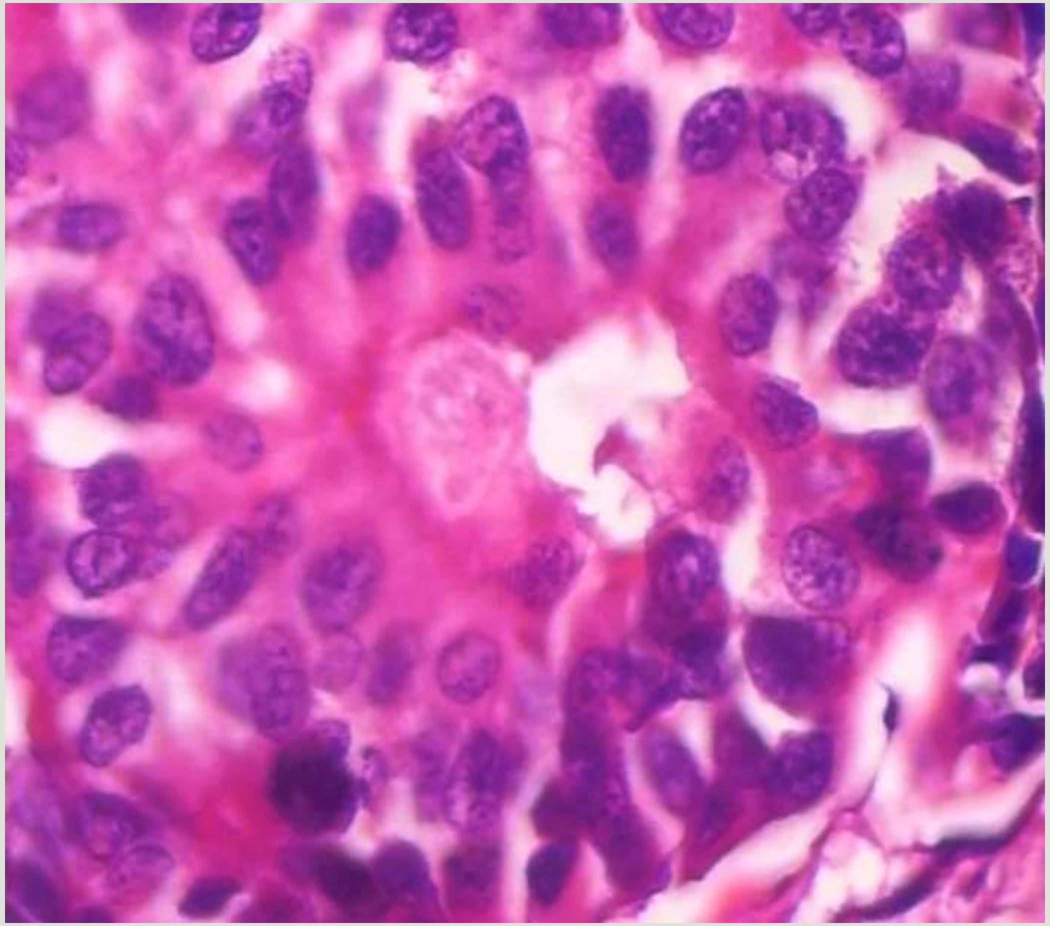
Zoom Range = 400x.

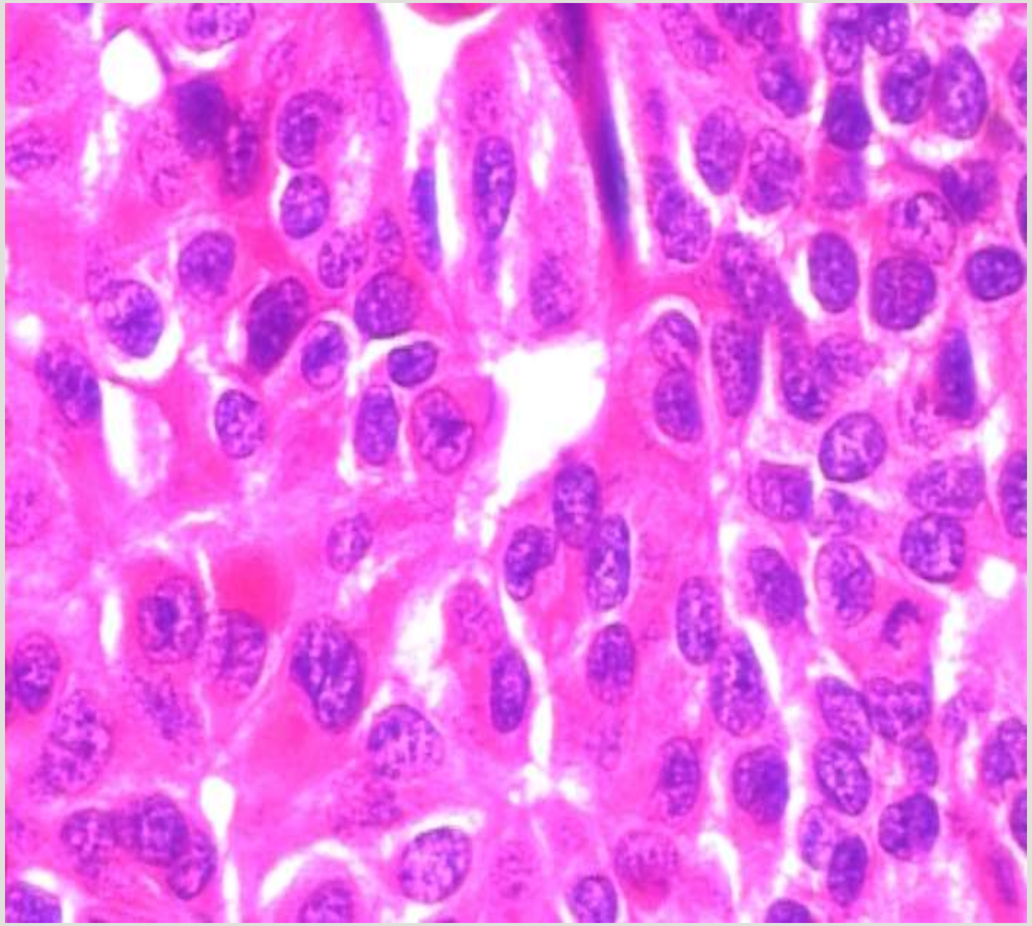
Dataset(Examples)





Dataset(Examples)





Evaluation Metrics

- Classification Metrics

a) Accuracy

b) Precision

c) Recall

d) F1 Score

- Rating and Preference Judgment.

a) Rating Image Quality

b) Real/Fake

Evaluation Metrics(Cont.)

- Fully Convolutional Network Metrics

a) Intersection-Over-Union(IOU)

b) Average-Per-Pixel Accuracy

c) Average-Per-Class Accuracy

- Image Quality Measures

a) Structural Similarity Index Matrix(SSIM)

b) Peak-Signal-Noise Ratio(PSNR)

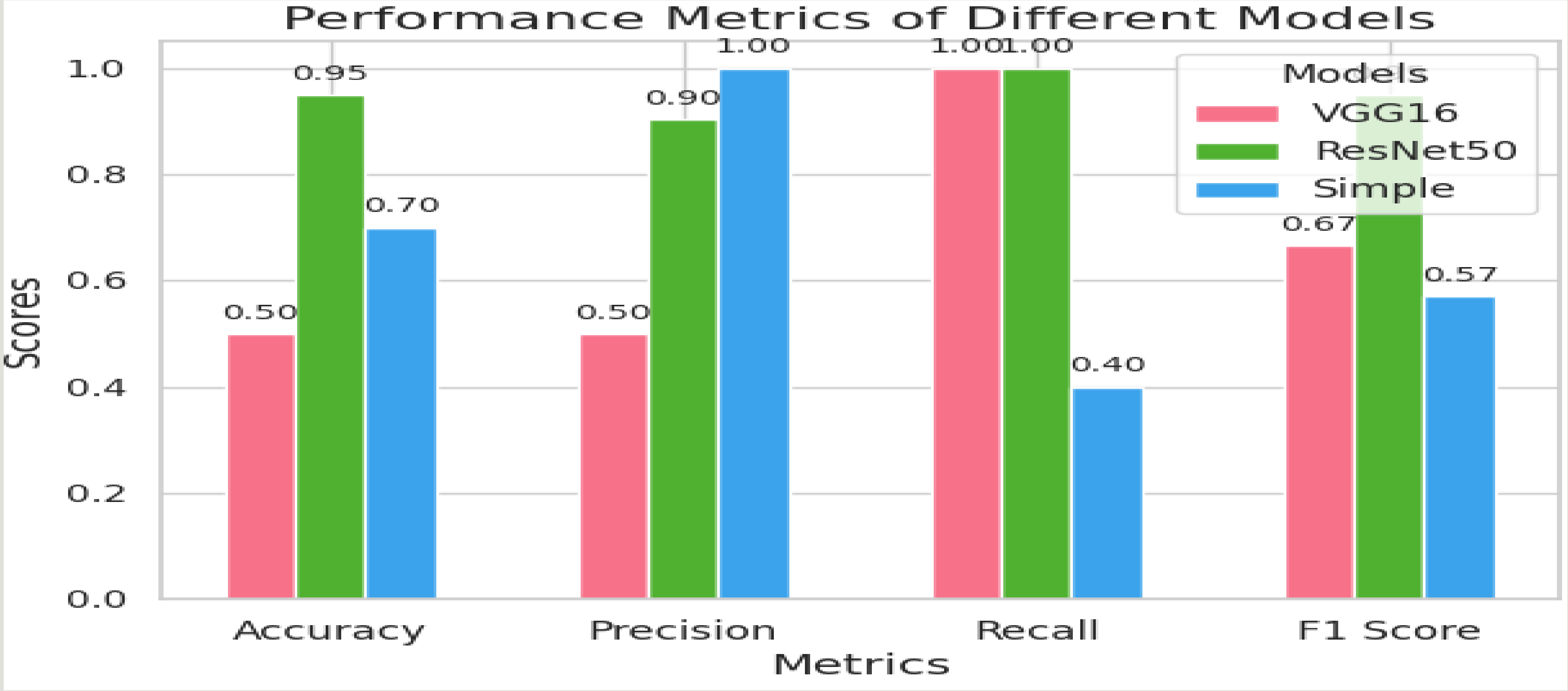
c) Mean Squared Error(MSE)

Results

Classification Metrics :

Model	Accuracy	Precision	Recall	F1 Score
VGG-16 CycleGAN	0.5000	0.5000	1.0000	0.67
ResNET-50 CycleGAN	0.9500	0.9036	1.0	0.95
Simple CycleGAN	0.70	1.0	0.400	0.57

Classification Results

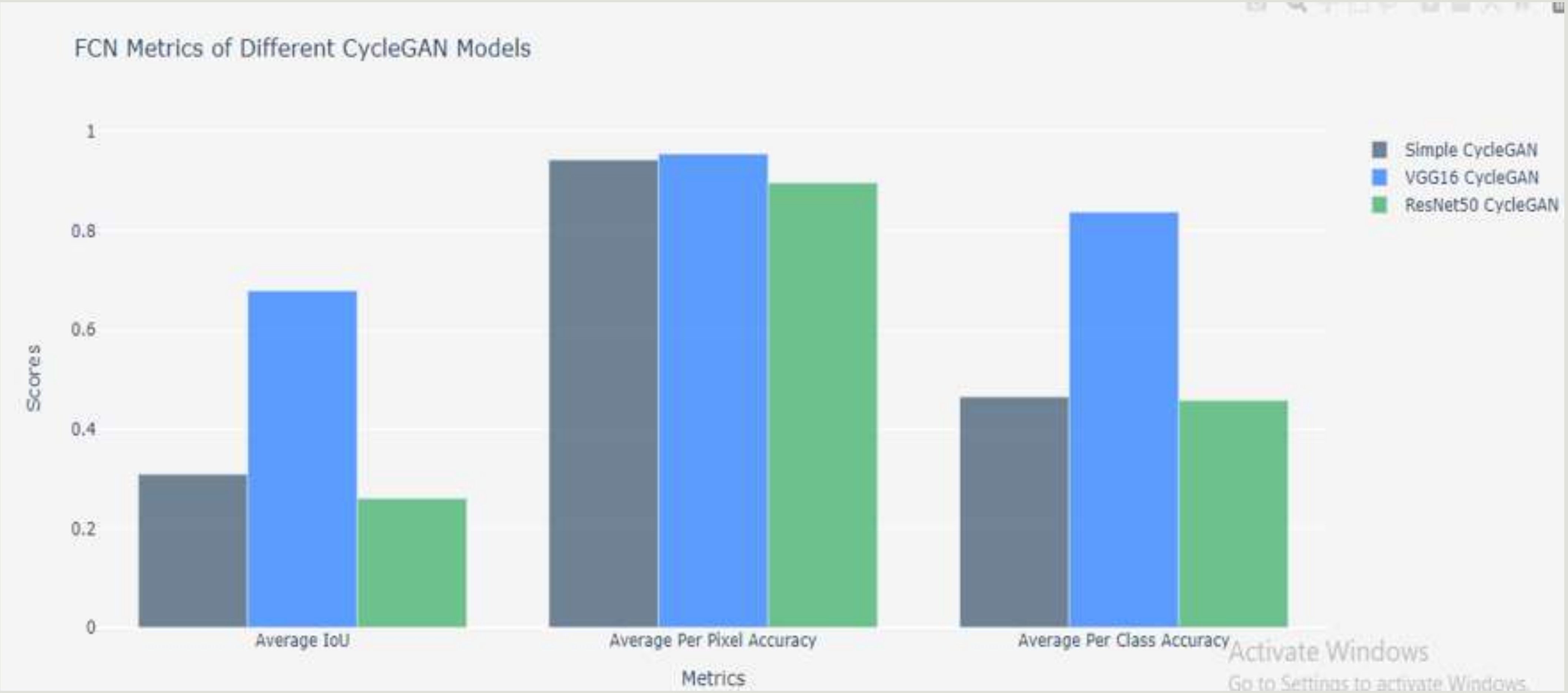


Results(Cont.)

FCN Results:

Model	Intersection over Union (IoU)	Average Per-Pixel Accuracy	Average Per-Class Accuracy
Simple CycleGAN	0.3091	0.9426	0.4653
VGG-16 CycleGAN	0.6787	0.9547	0.8374
ResNET-50 CycleGAN	0.2603	0.8962	0.4578

FCN Results:


FCN Metrics of Different CycleGAN Models
Simple CycleGAN
VGG16 CycleGAN
ResNet50 CycleGAN
Scores
1
0.8
0.6
0.4
0.2
0
Average IoU
Average Per Pixel Accuracy
Average Per Class Accuracy
Metrics
Activate Windows
Go to Settings to activate Windows.

Results(Cont.)

Image Quality Measures :

SSIM:

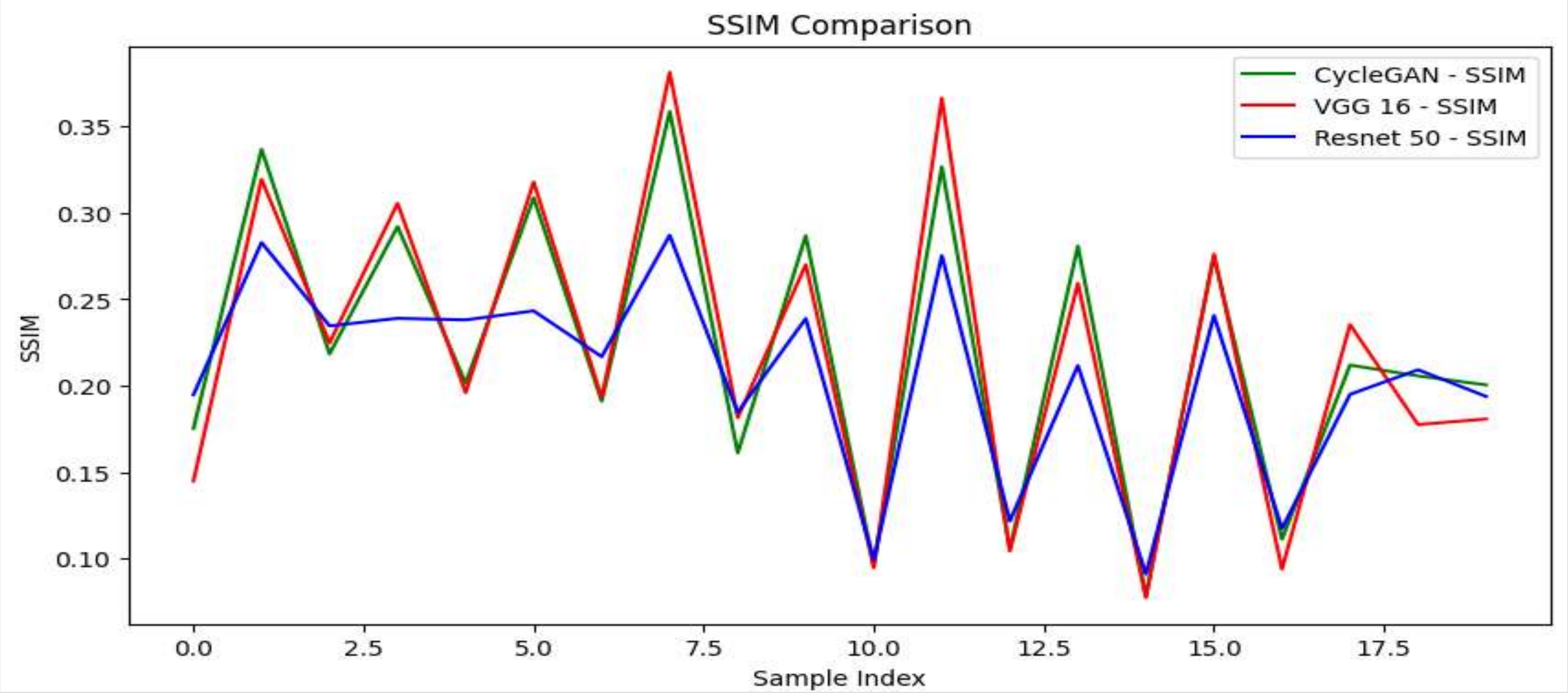


Image Quality Measures(cont.)

PSNR :

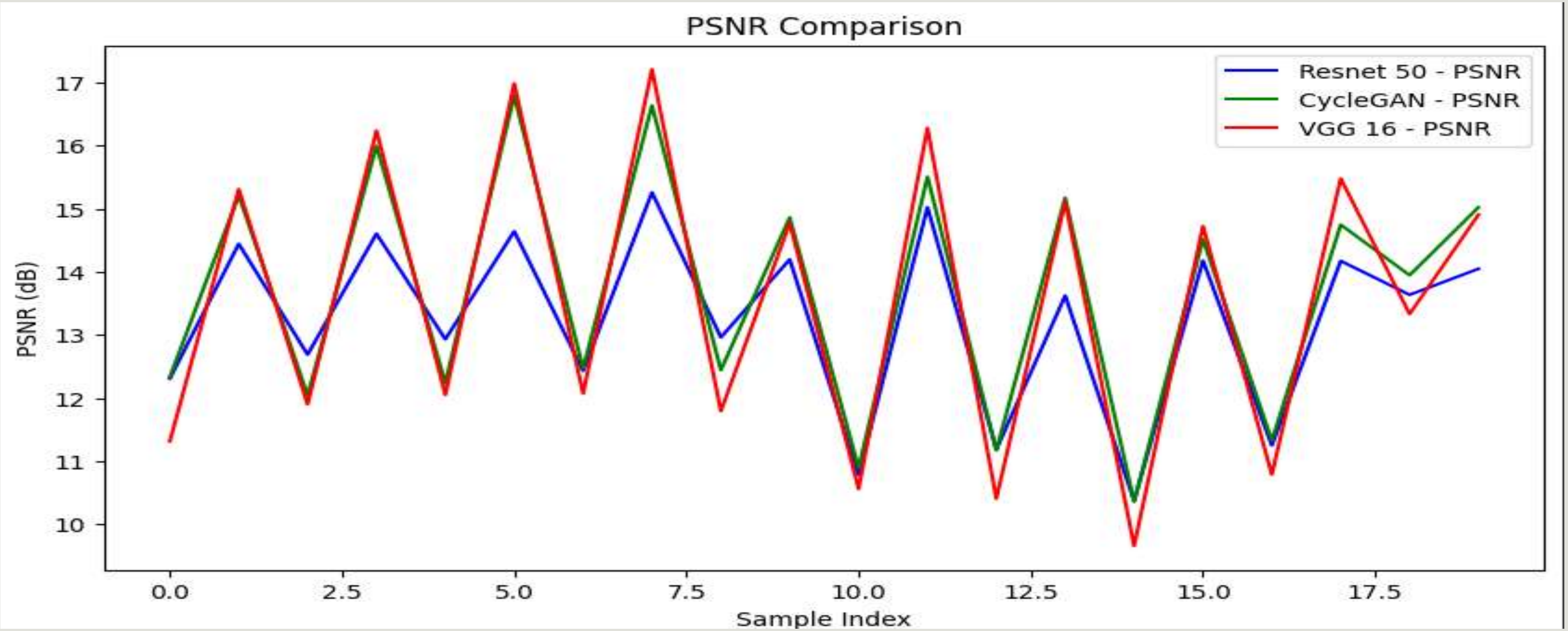
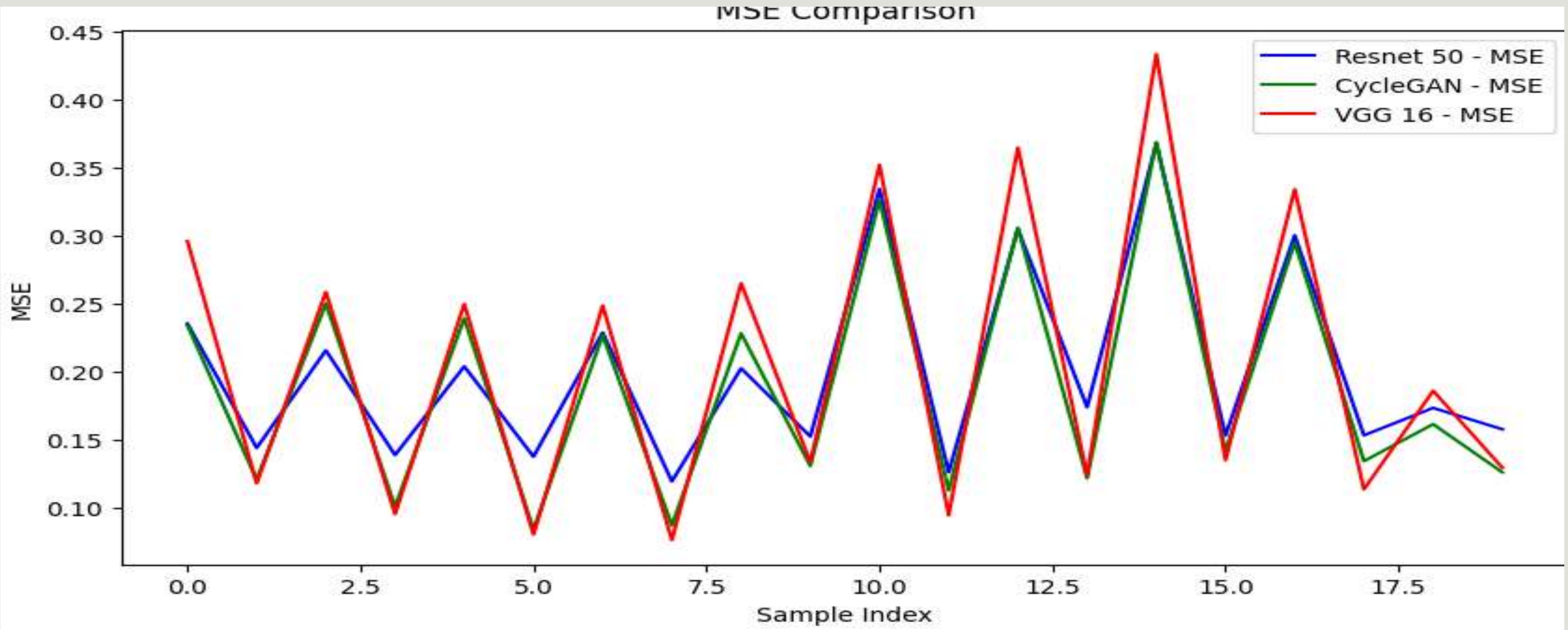


Image Quality Measures(Cont.)

MSE :



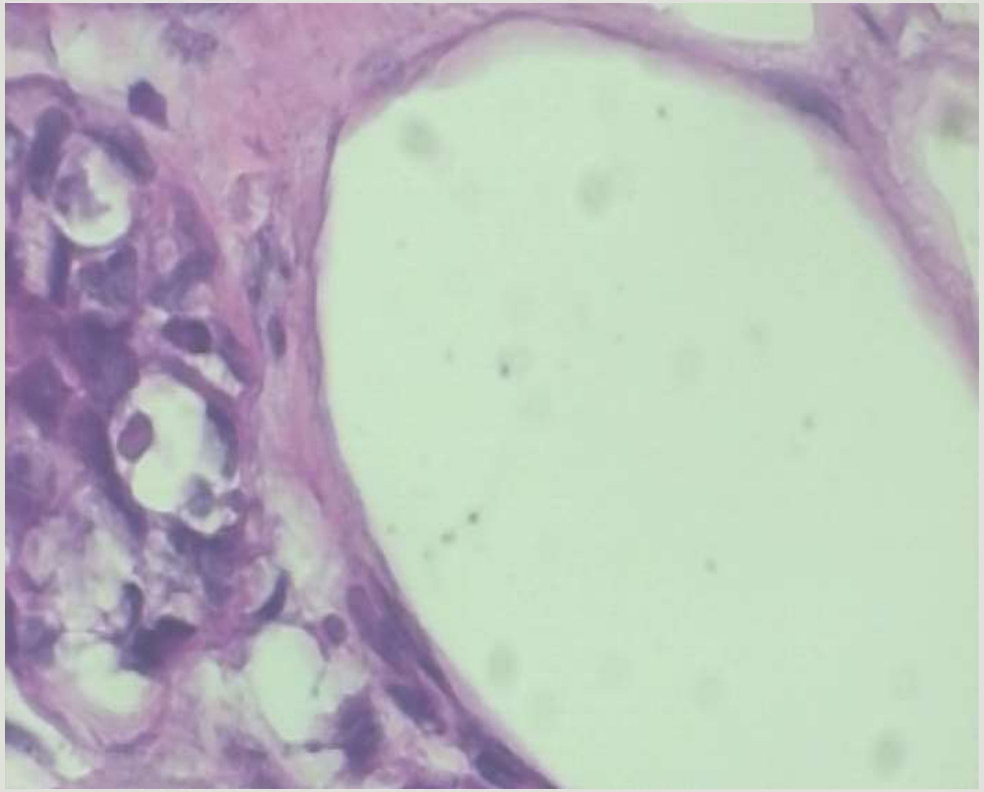
Results(Cont.)

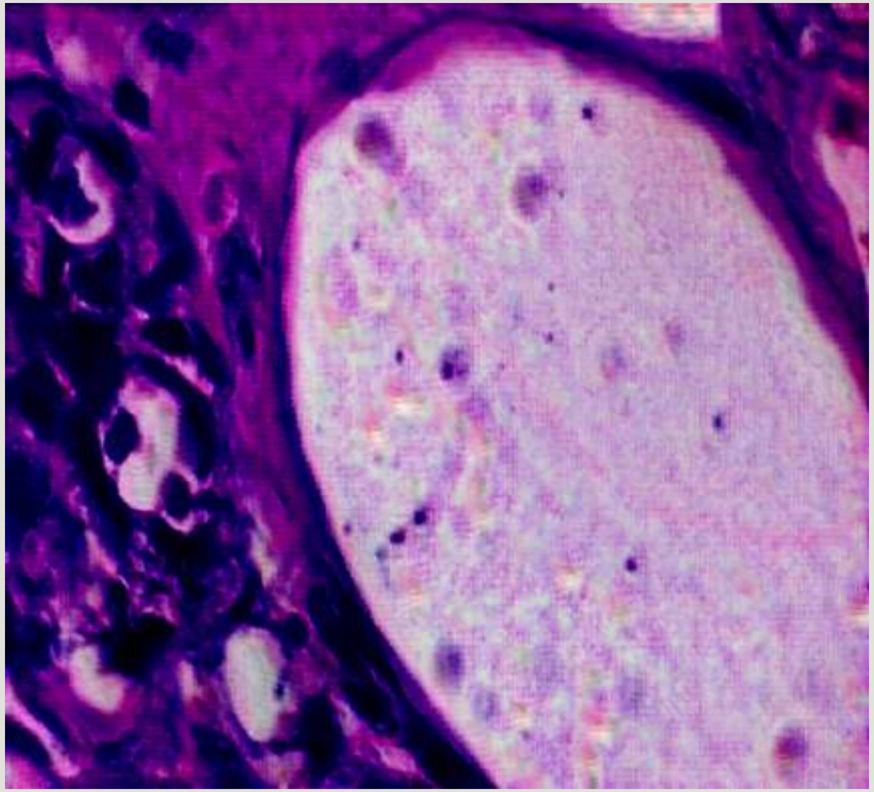
Rating and Preference Judgment :

Model	Average Image Quality	Real/Fake(%)
Simple CycleGAN	3.51	0.80
VGG16 CycleGAN	4.2	0.95
ResNet50 CycleGAN	2.85	0.50
Real Images	3.9	0.90

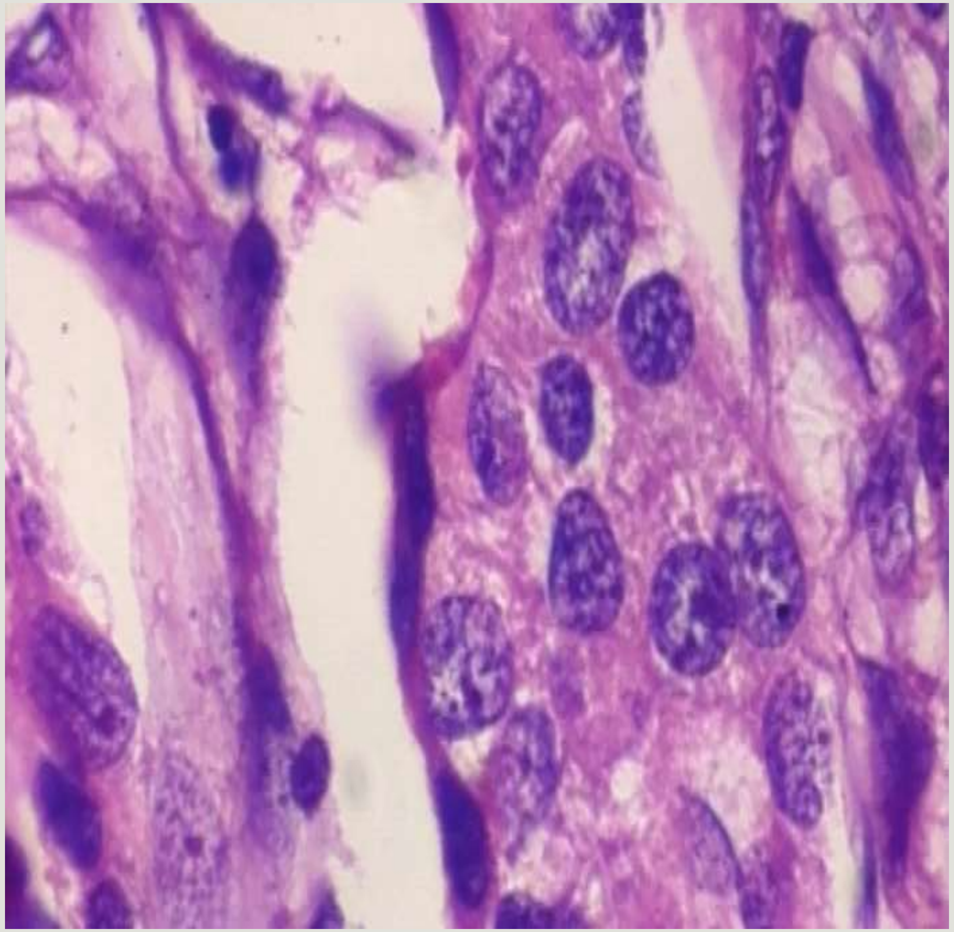
Real Vs Generated Examples

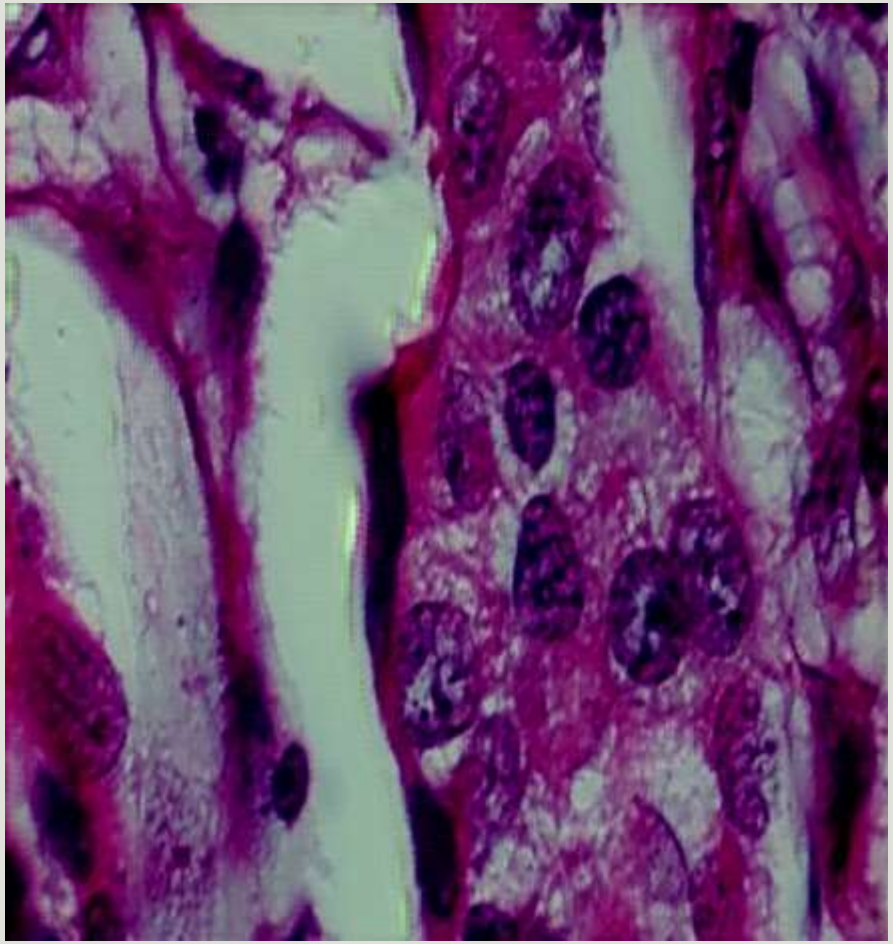
Simple Cycle GAN:





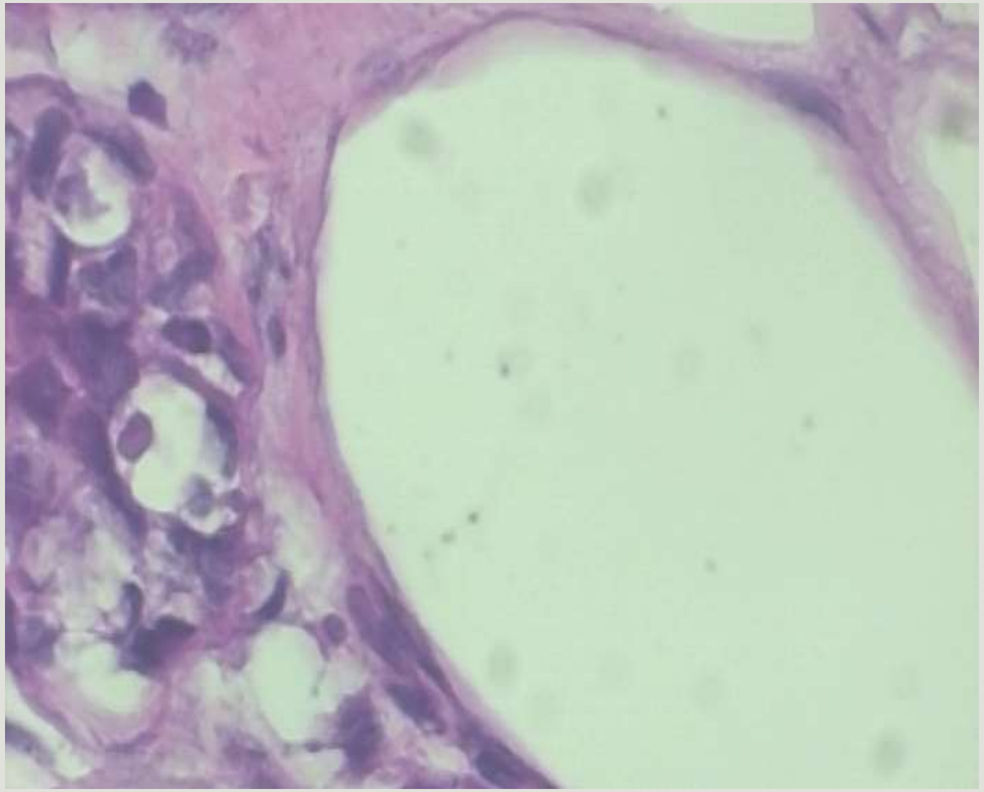
Real Vs Generated Examples

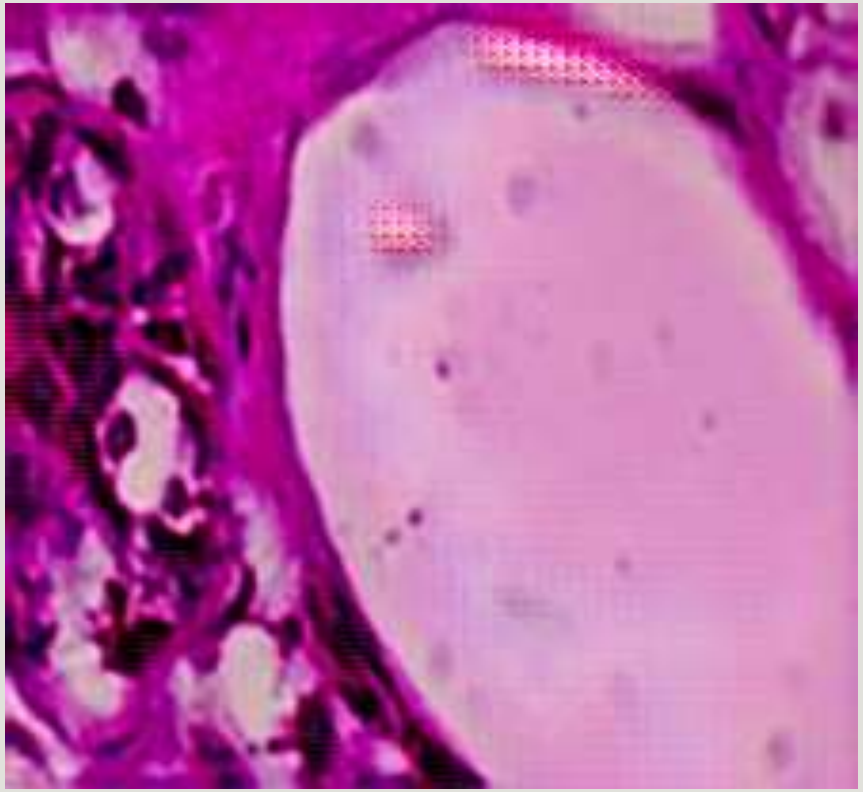




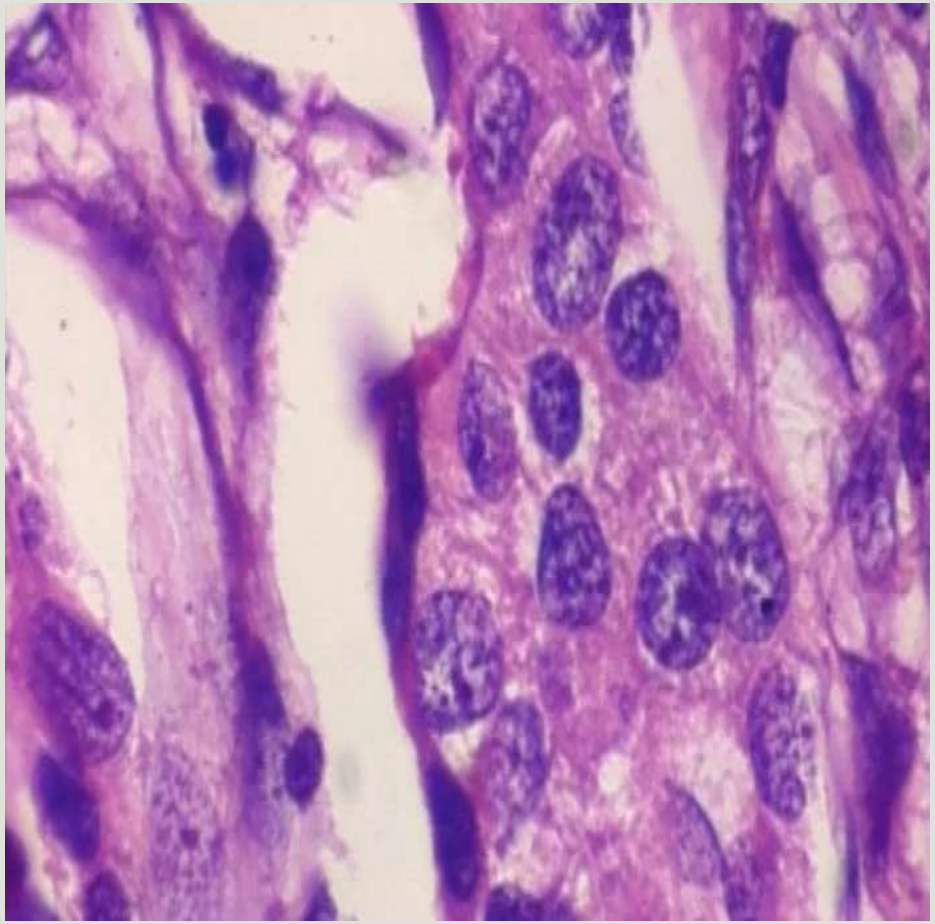
Real Vs Generated Examples

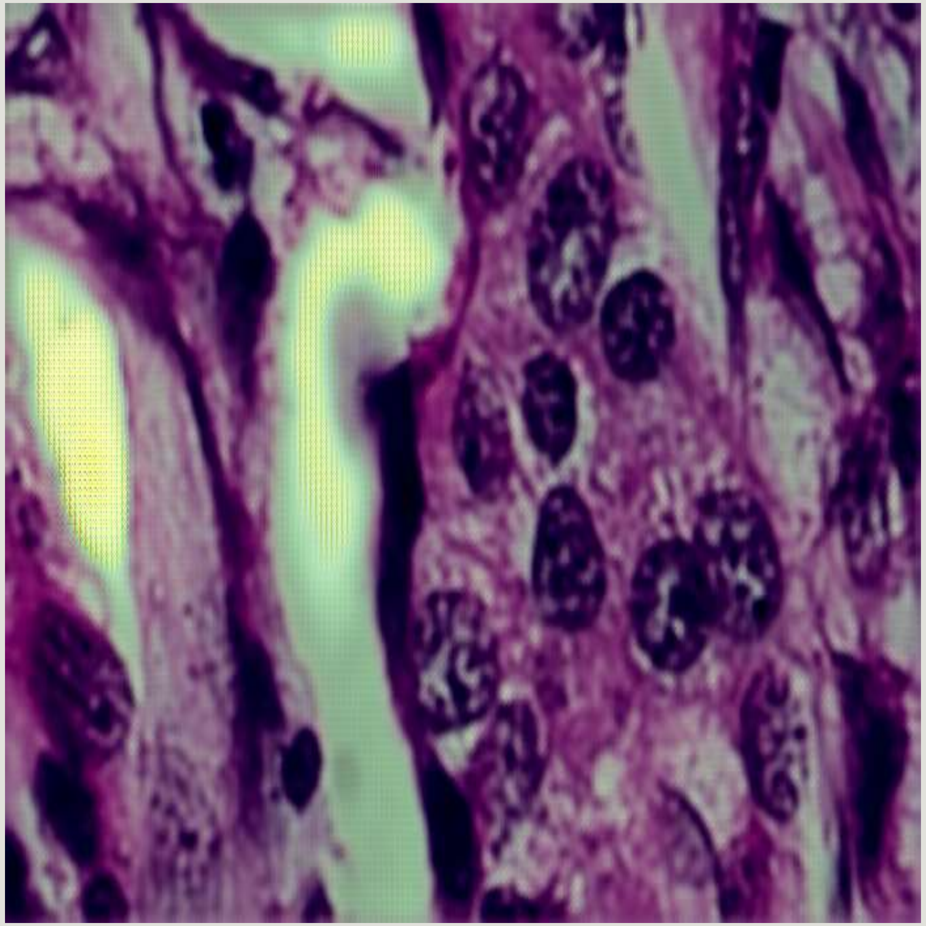
VGG-16 Cycle GAN:





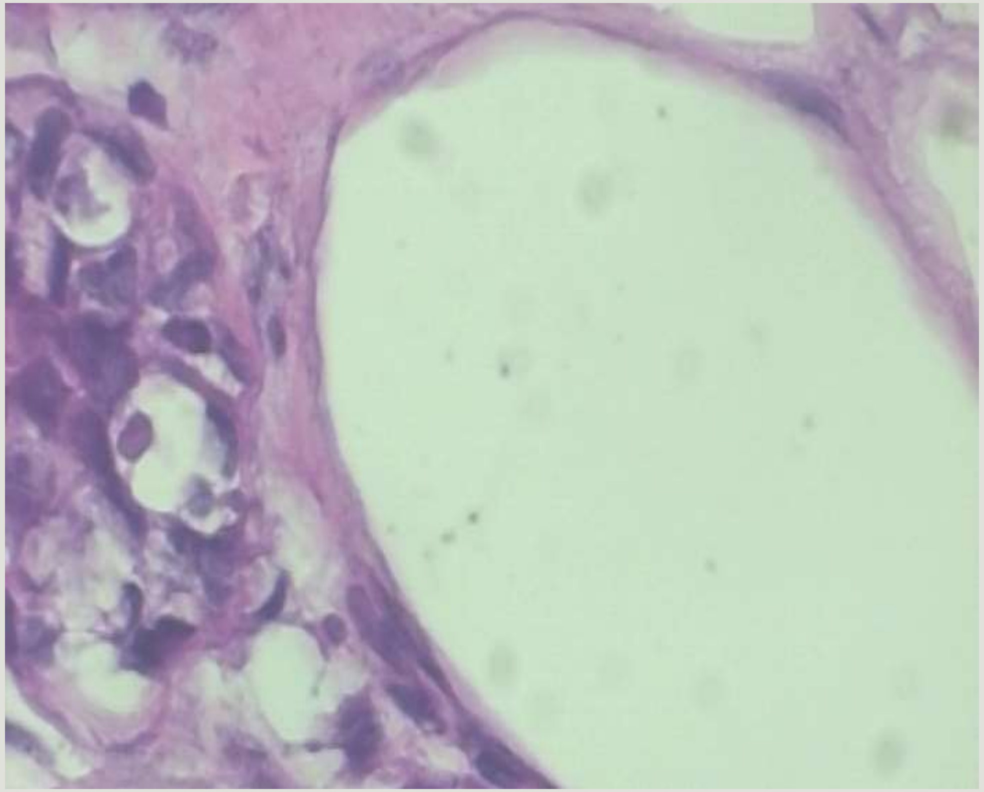
Real Vs Generated Examples

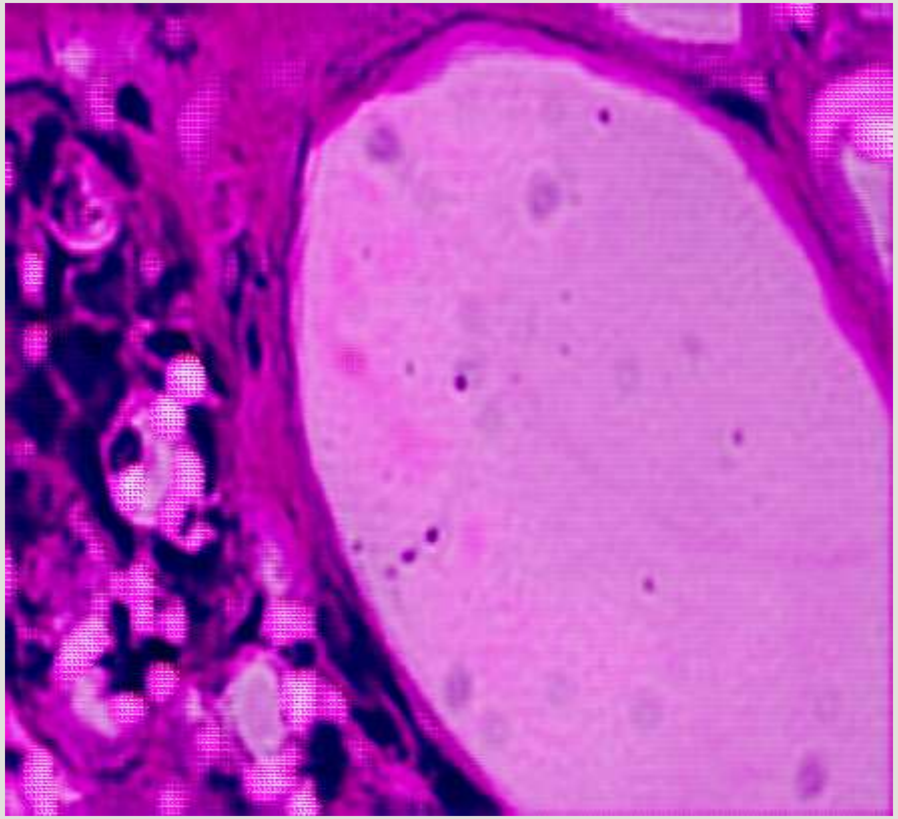




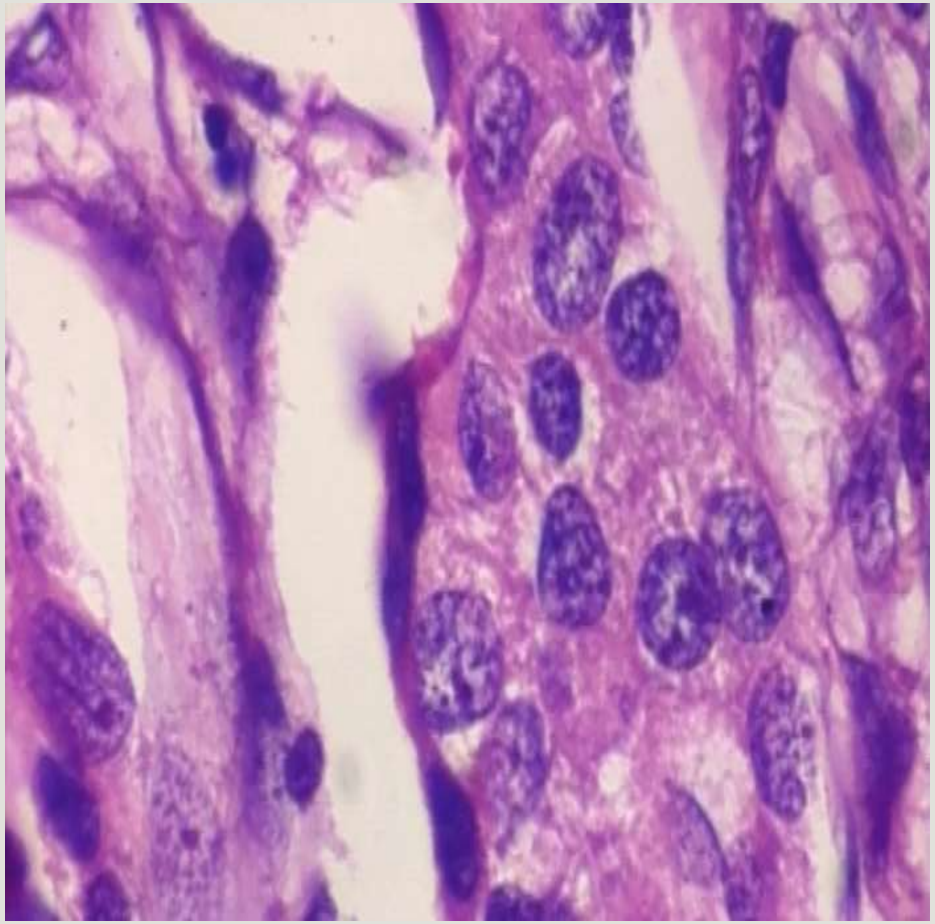
Real Vs Generated Examples

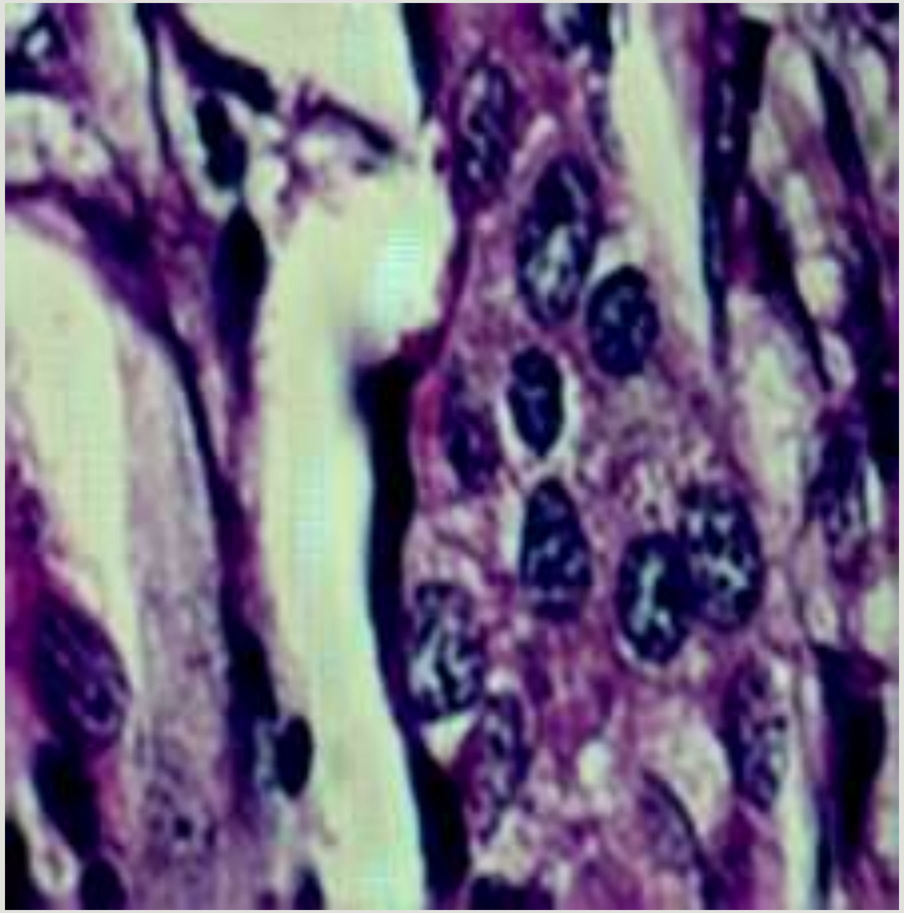
ResNET-50 :





Real Vs Generated Examples





Tools/Simulators :

- Python
- Pytorch
- Scikit Learn
- Matplotlib
- Seaborn
- Google Colab
- Google Drive
- Pycharm
- Anaconda Jupyter Notebook
- BreakHis Dataset

Limitations :

- The generated images often contain noticeable noise and artifacts, affecting quality and realism.
- Significant computational power is required, limiting accessibility for researchers with constrained resources.
- Training deep models is time-intensive, often taking several hours to days.
- A substantial amount of labeled data is still needed, which is time-consuming and costly to acquire.
- The models may not generalize well across different medical imaging modalities and tumor types, needing further validation.

Thank You