Using GANs and Encoders/Decoders for Image-to-Sketch Translation

15.S04: Hands on Deep Learning

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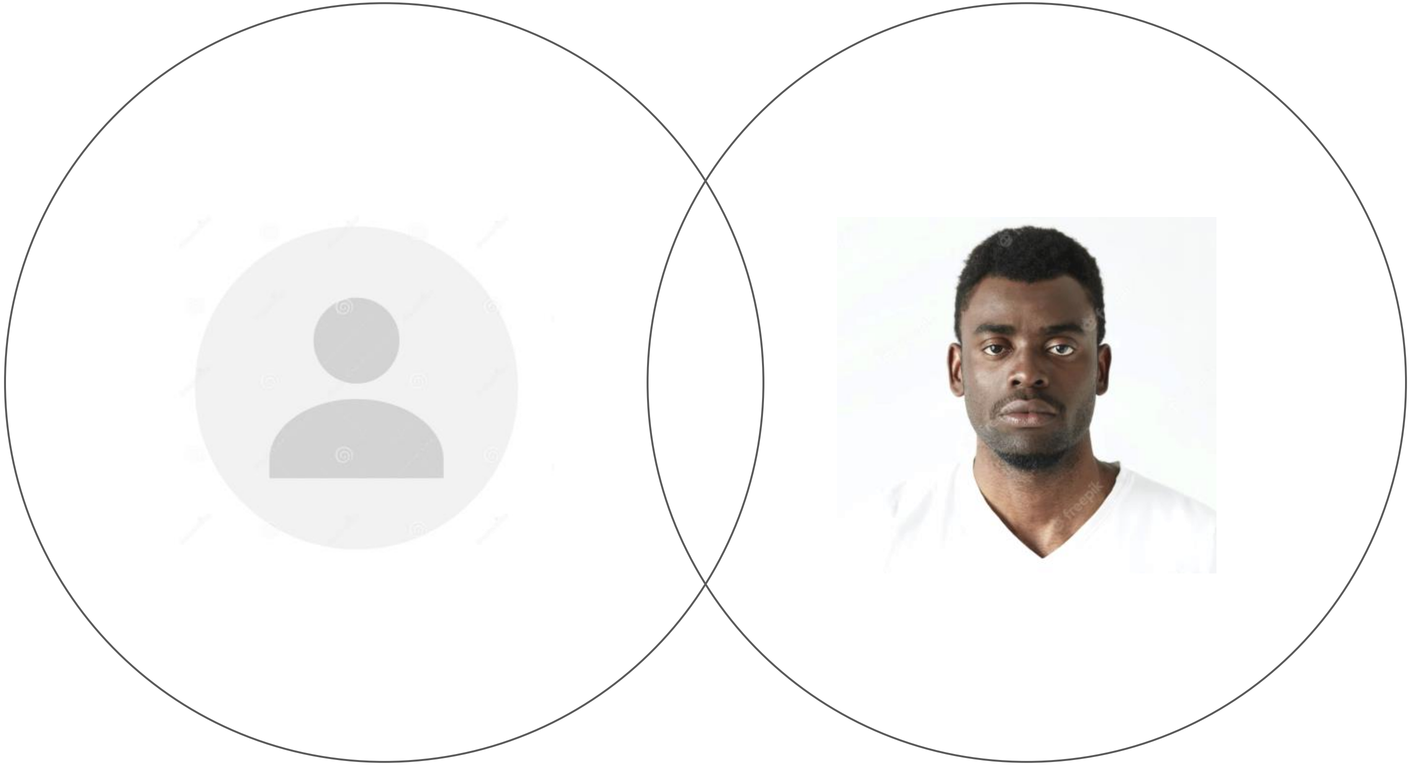
Introduction

Preservation of Privacy

Accurate Expression of Self



Memoji

Apple

Messaging and
communication

Digital People

Soul Machine

AI customer
service, virtual
assistant

Digital Humans

Uneeq

Frontend application
for chatbots

Objective: Convert Photographs to Sketches

Goal is to automate avatar creation within 2 dimensions, limited to grayscale

facial photograph

deep learning model

corresponding sketch

Data

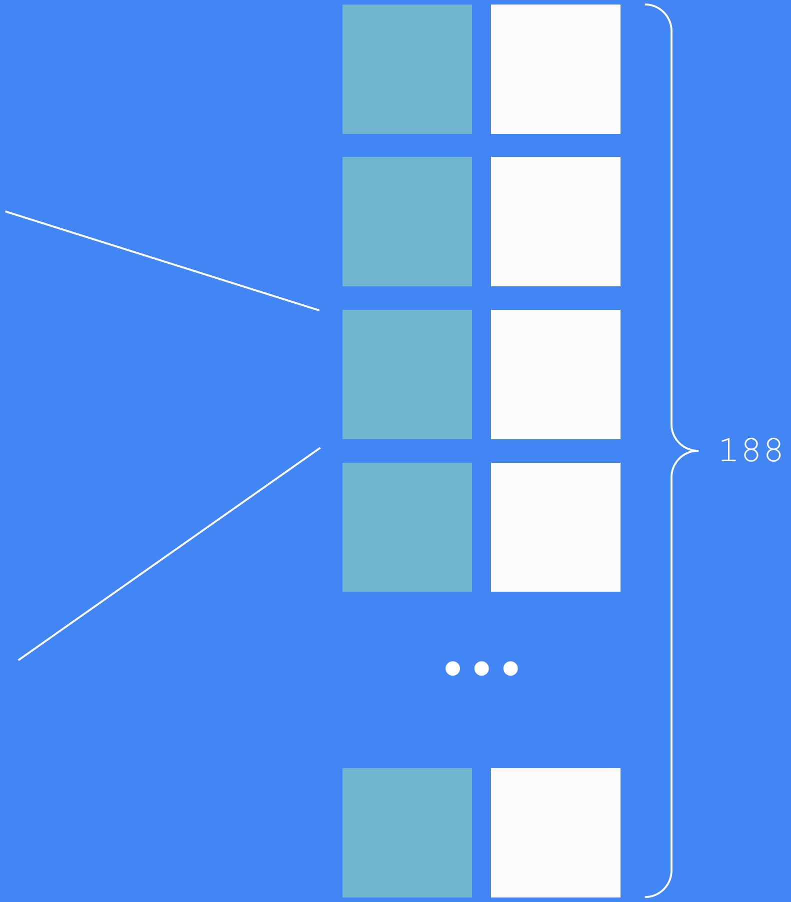
Dataset

photograph

shape: (256, 256, 3)

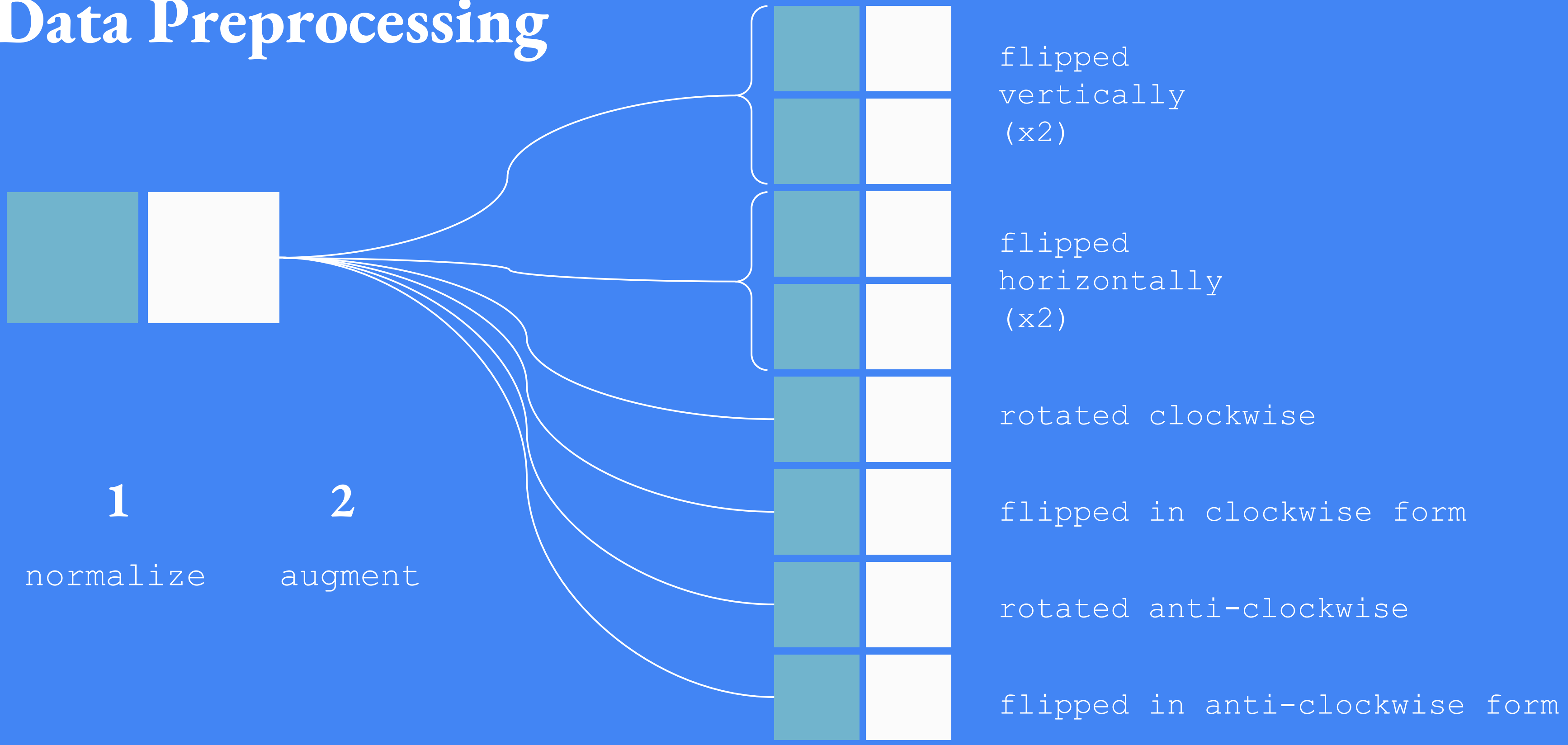
sketch

shape: (256, 256, 3)



Data collected from Chinese University of Hong Kong, publicly available on Kaggle!

Data Preprocessing



1

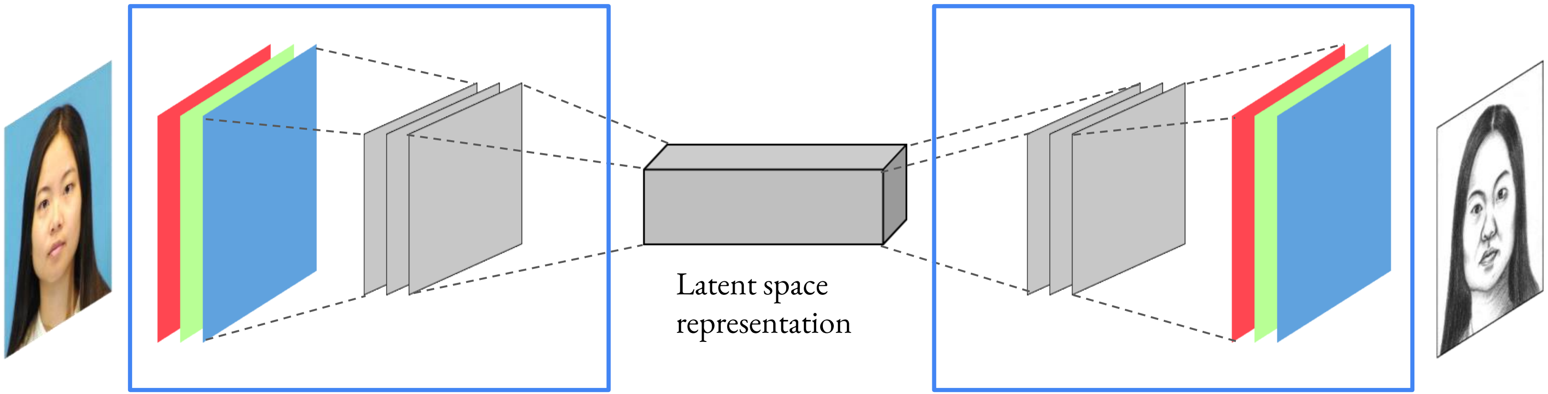
normalize

2

augment

Methodology

Method 1: Encoders / Decoders



Encoders

- Extract meaningful features & create a compressed representation
- A series of convolutional layers that capture hierarchical patterns and structures in the input image

Decoders

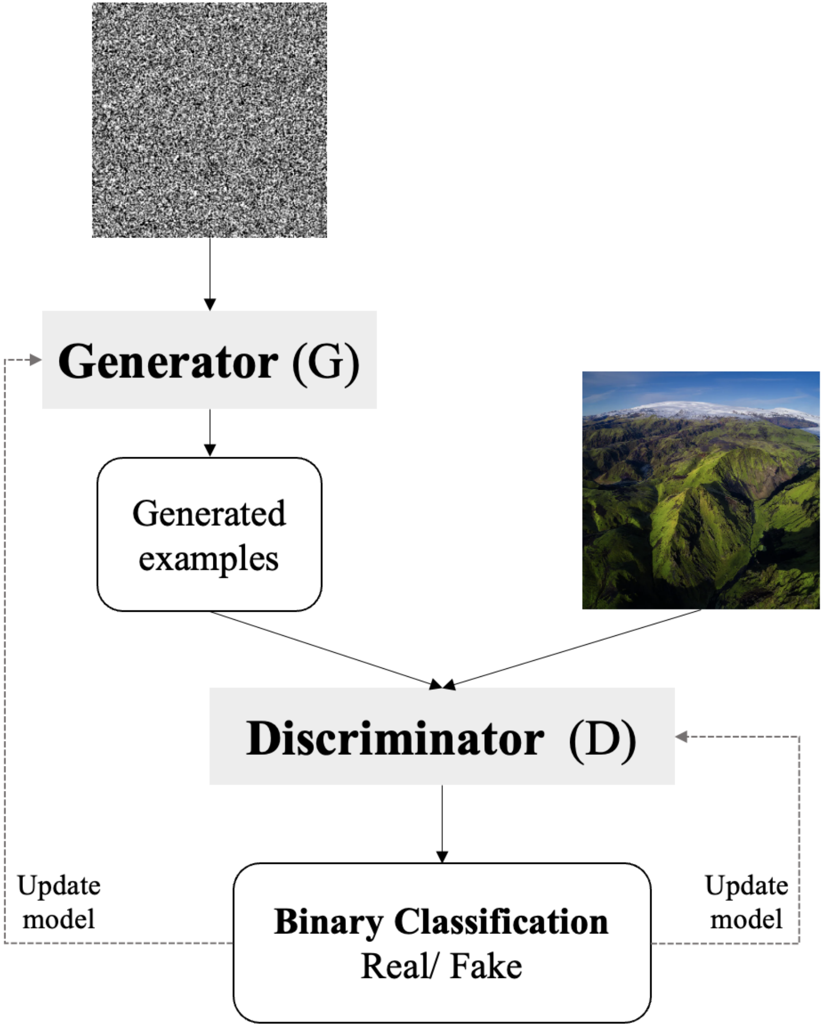
- Take the compressed representation and reconstruct a new image based on the extracted features
- A series of upsampling and convolutional layers to gradually increase the spatial resolution of the output image

Method 2: cycleGAN

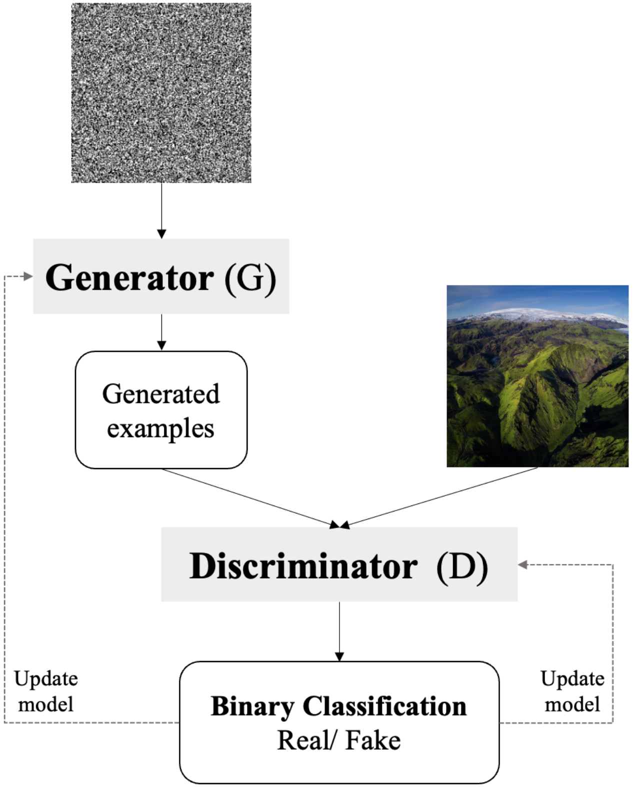
GAN (Generative Adversarial Networks)

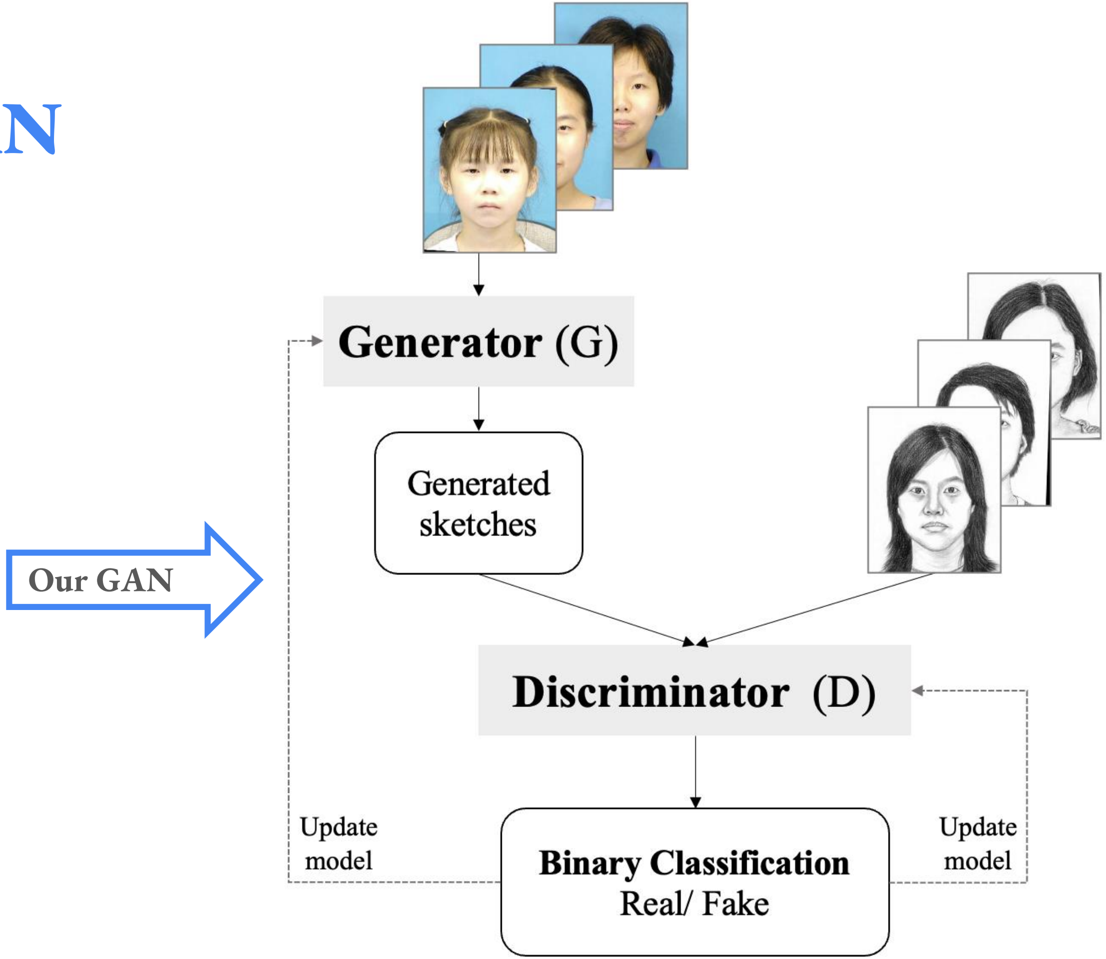
Generate images

- **GENERATOR** → Generates synthetic images
- **DISCRIMINATOR**
  - **Input** → Real image vs Synthetic images
  - Evaluates the authenticity of the generated data
- Trained simultaneously through **adversarial training**
- **Backpropagation** → update weights



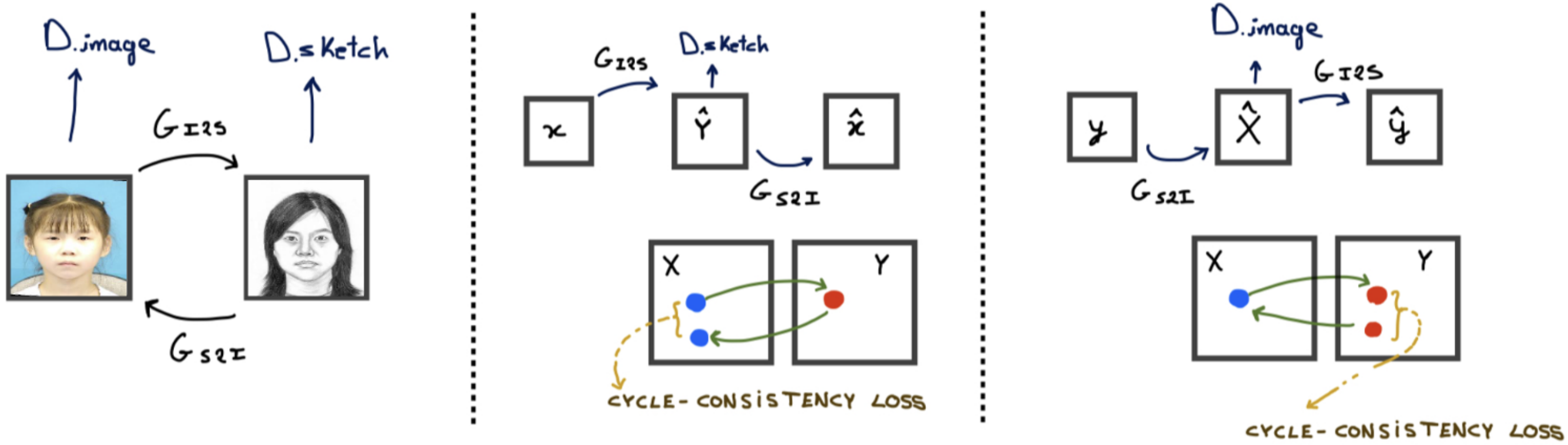
Method 2: cycleGAN





Method 2: cycleGAN

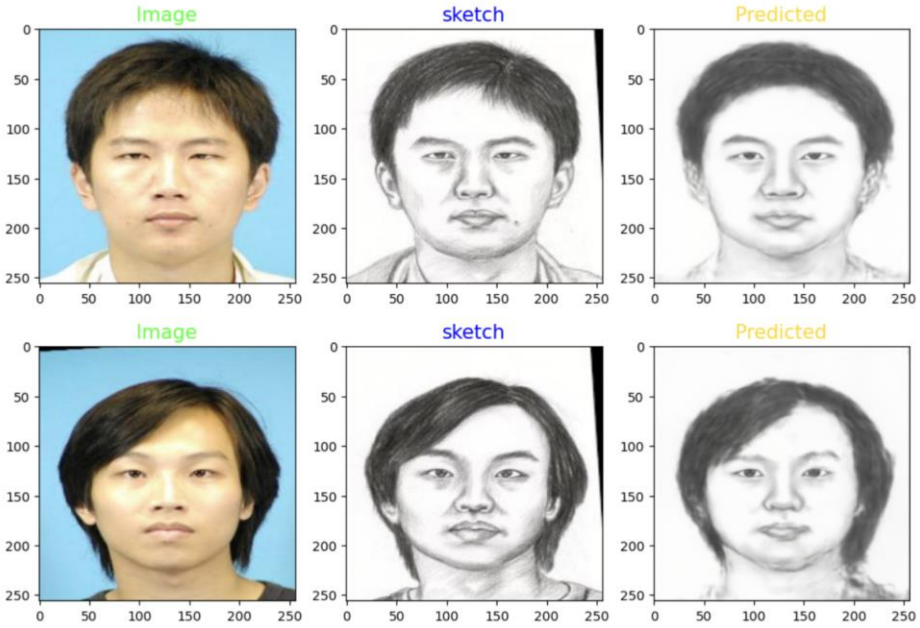
- Unpaired image-to-image translation
- **2 GANs** → (**I2S**) GAN is responsible for generating sketches from images *and* (**S2I**) the other GAN generates images from sketches



- **Consistency loss** → Enforces the constraint that **if an image is translated from one domain to another and then back again**, it should closely **resemble the original image**

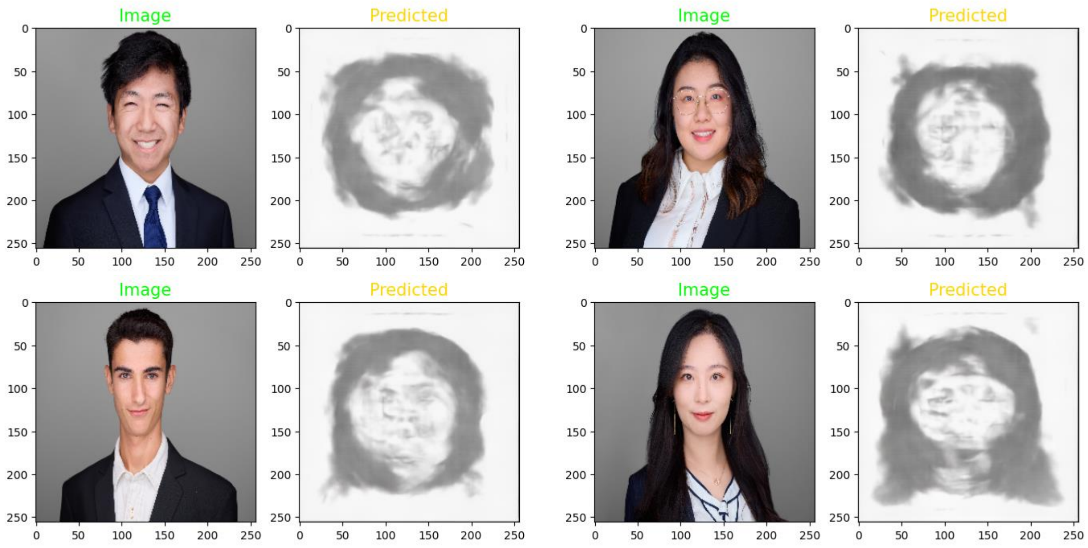
Results

Result I - Encoder & Decoder



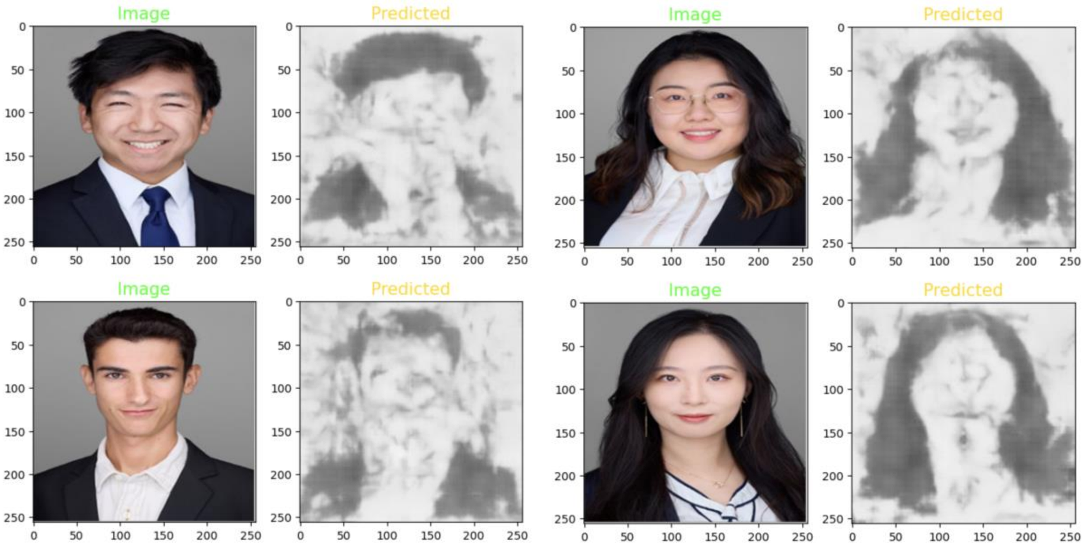
- Predictions have high resemblance to the original sketches.
- While some details of brushstrokes are lost, the model is able to reconstruct the original human faces clearly.

Result II - Encoder & Decoder (Incomplete Training)



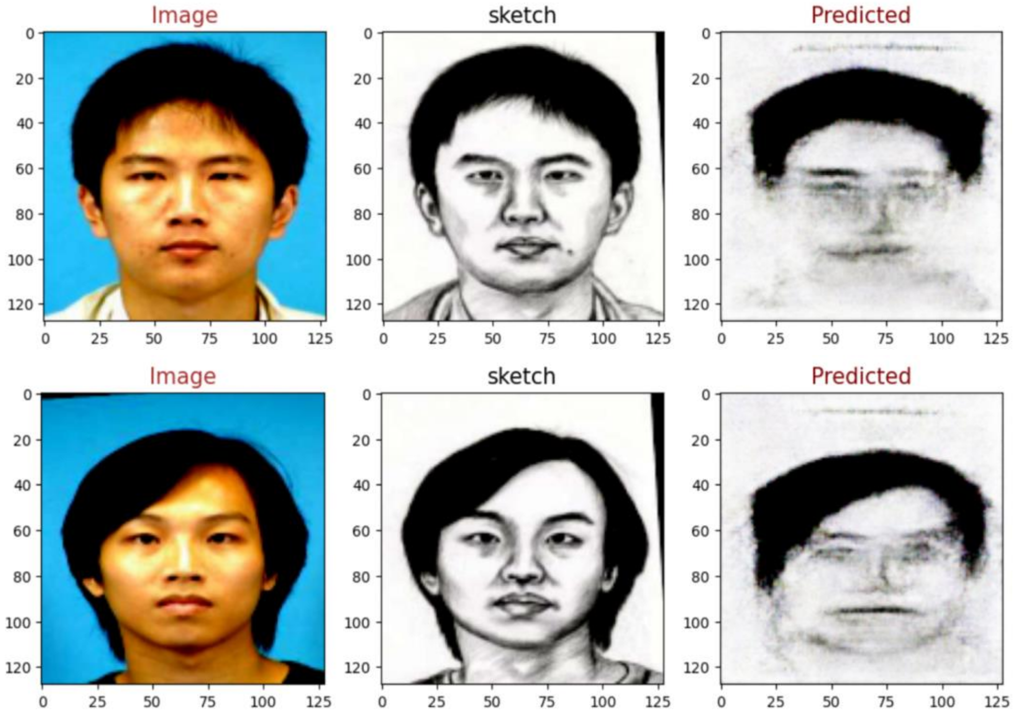
- Model struggles to capture specificities for each face, seems to output an averaged representation of all faces in its training data

Result II - Encoder & Decoder (Complete Training)



- Model captures the most obvious features of the photos, for example, the area with the darkest colors like hair and clothes.
- It fails to capture the details in the face area.

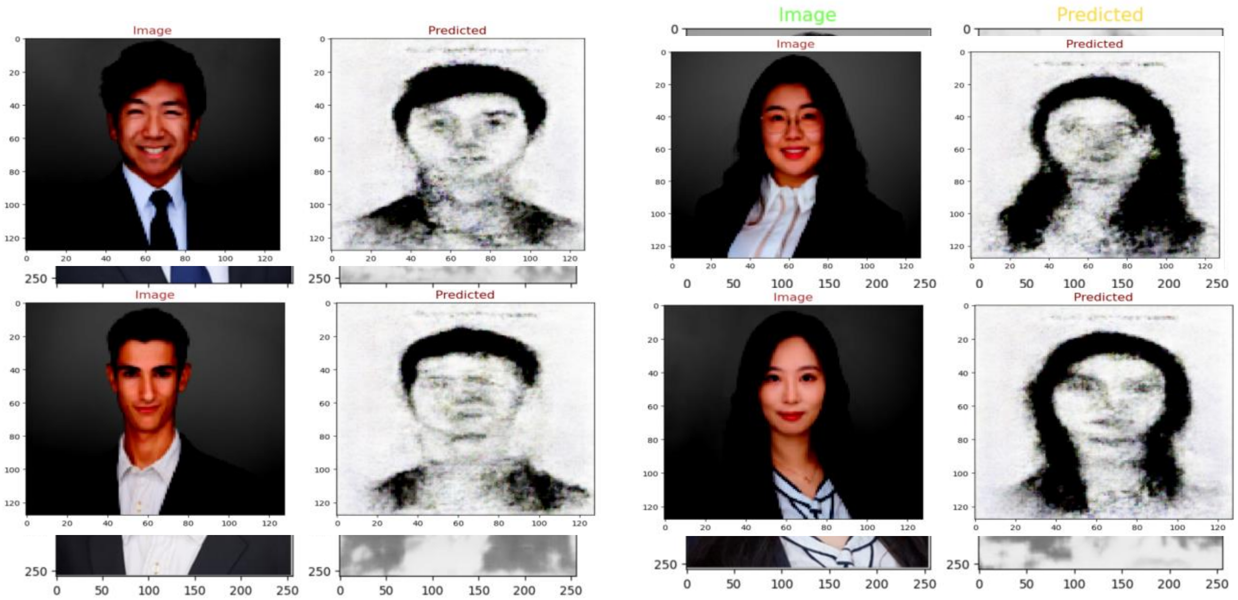
Result III - cycleGAN



- Sketches predicted from random samples with the generator G_{I2S}
- Blurred
- Worse off compared with Encoder/Decoder methods - abstract facial features & hair shape

Result IV - Best Model for new images (cycleGAN)

photograph sketch photograph sketch



- New image with different styles and lighting conditions
- Better off compared to Encoder/Decoder method
- Slightly worse off compared to same testing dataset for cycleGAN

Result V - Sketches to Images Generation

- Images predicted from random sketches with a different generator G_{S2I}
- blurred

Lessons Learned

Overfitting

Lack of diversity in the training dataset (style, race, lightening...)

Insufficient training data and training time