Ghiblify! Cartoonizing Images Using GANs



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Introduction

Anime artists painstakingly recreate real-life scene through hand-drawn sketches for full-feature anime film. Could artificial intelligence become part of the anime creation workflow?



Project Objective

- Explore how GANs can assist in cartoonizing real-life images for anime artistes and serve as a fun application for social network apps
- Understand how to optimize GAN hyperparameters and architecture for the best results for cartoon style transfer

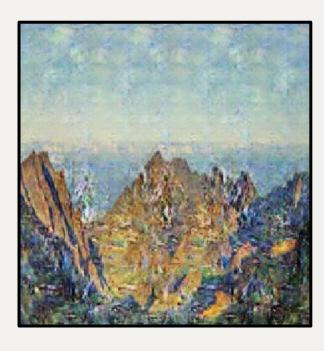
Style Transfer



Content Mountain

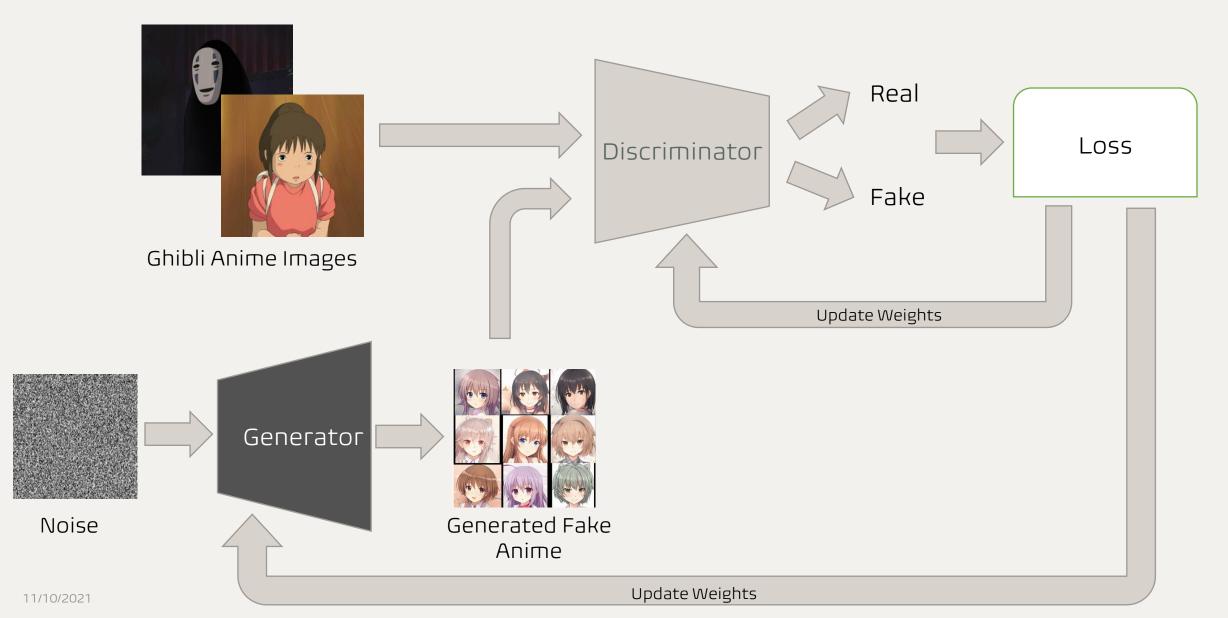


Style Monet Painting



Target

Generative Adversarial Networks



E

Analysis Methodology

Image Curation Image Preprocessing Train GAN Models Select Best Models

- Real-Life Images
- Anime Images
- Images Themes

- Image Size
- Image Aspect Ratio
- Basic GAN
- CycleGAN
- Unsupervised
- TuneHyperparameter
- Adjust architecture
- Qualitative review of generated anime

Images Data

Image Preprocessing

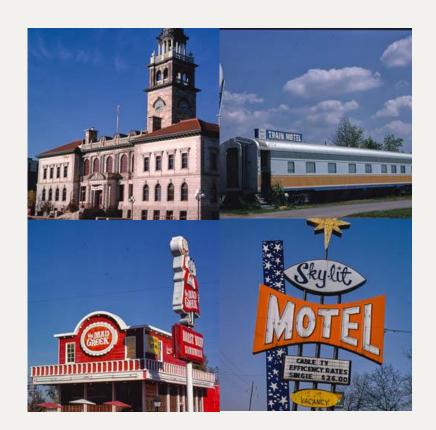


All images have been cropped to 1:1 aspect ratio and are either
 256x256 or 512x512 in size

Sample Images – Real-Life



6387 images Theme: Mixed Source: Unsplash



1976 images Theme: Architecture Source: Kaggle

Sample Images – Real-Life



3318 images Theme: Asian Female Portraits Source: Kaggle



11 images Theme: Asian Female Portraits Source: generated.photos

Sample Images – Anime



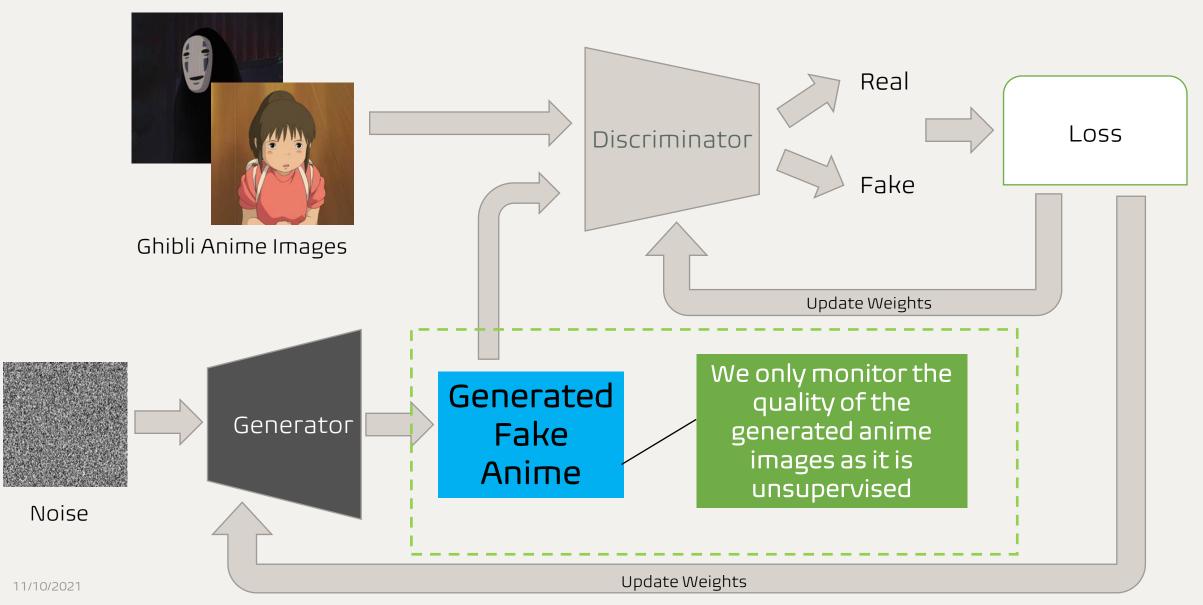
6079 images Theme: Mixed, Ghibli Source: Netflix



3400 images Theme: Female Portrait Source: Kaggle

Basic GAN

Basic GAN with Noise Input

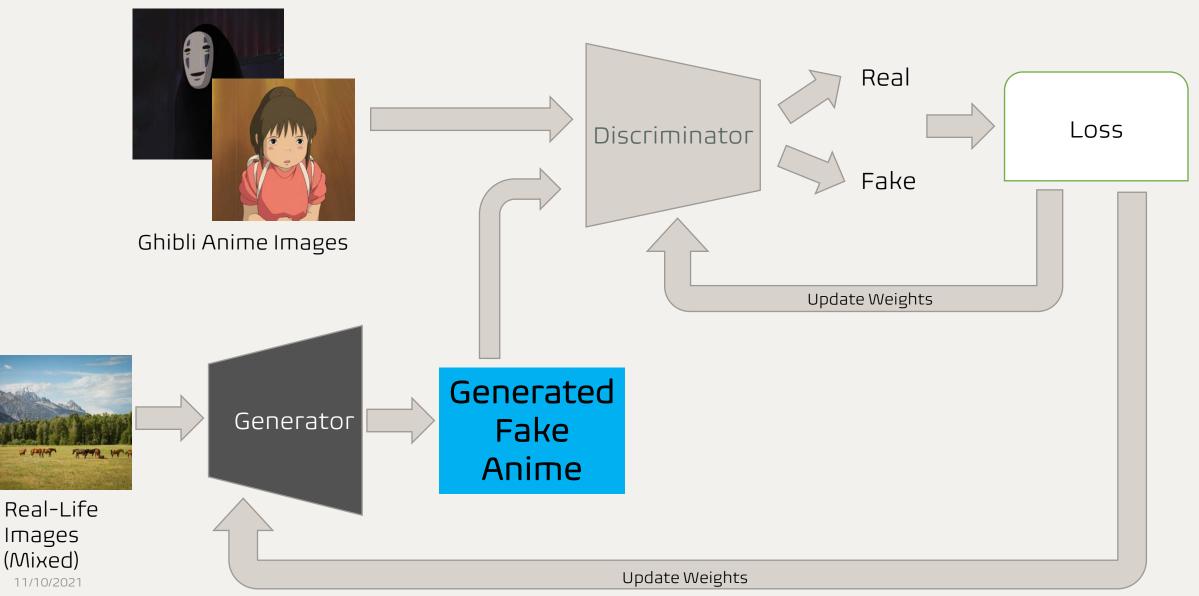


Basic GAN

Generated Anime images
 has the Anime style but
 with no clear content

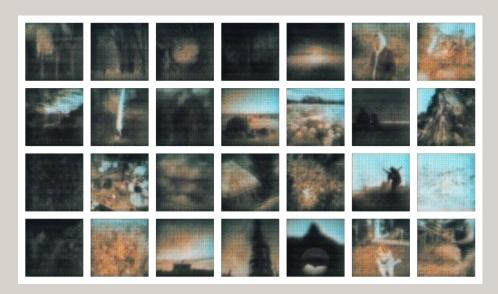


Basic GAN with Real Image Input

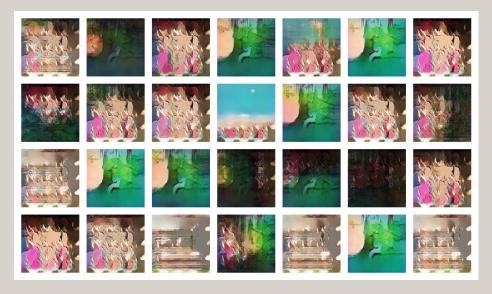


Basic GAN with Real-Life Image Inputs

- Content clearly visible in early epochs but were lost after 200 epochs
- Basic GAN does not have loss function to retain content
- Another GAN model required which transfer style and retains content



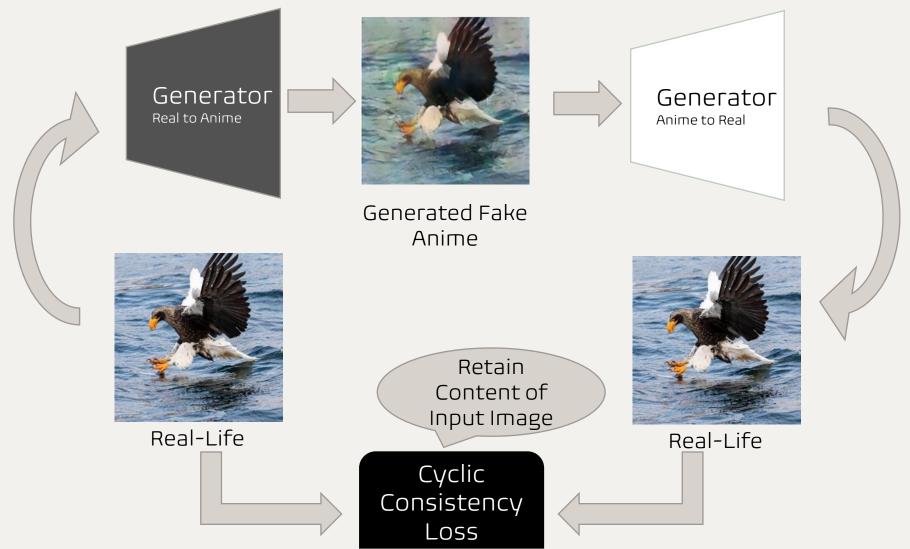
Generated Anime at 1st Epoch



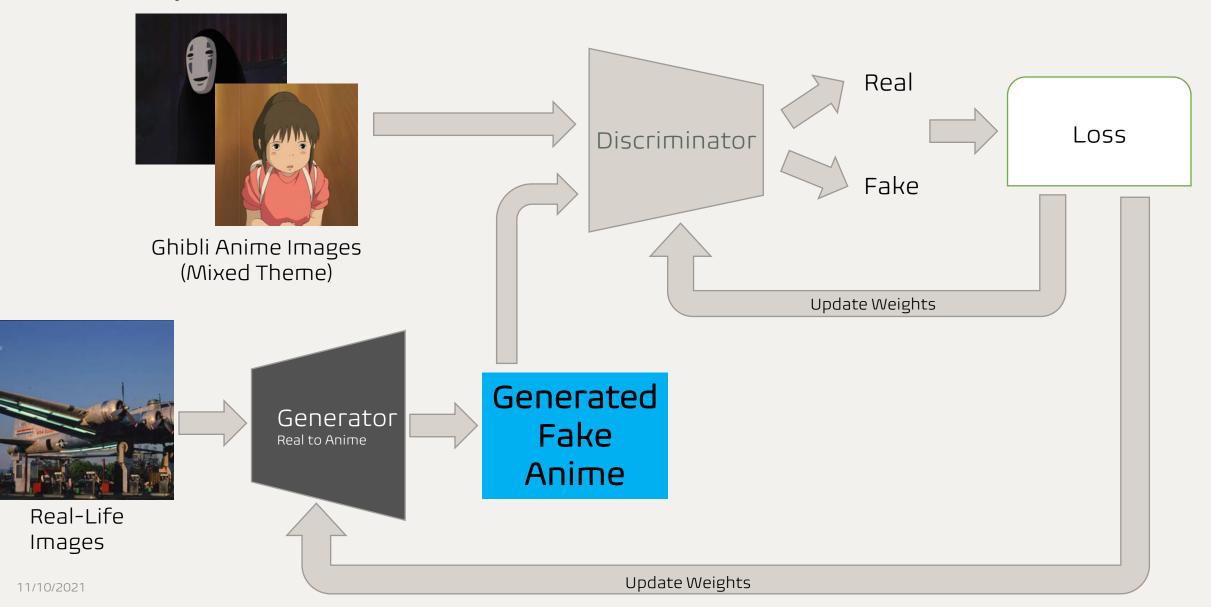
Generated Anime at 200th Epoch

CycleGAN

Introduction to CycleGAN



CycleGAN with Mixed Theme Anime



CycleGAN with Mixed Theme Anime

- Anime style successfully transferred on most images
- The model generated incoherent patterns on some images with blue skies
- Anime training data set needs to be clean and of common theme

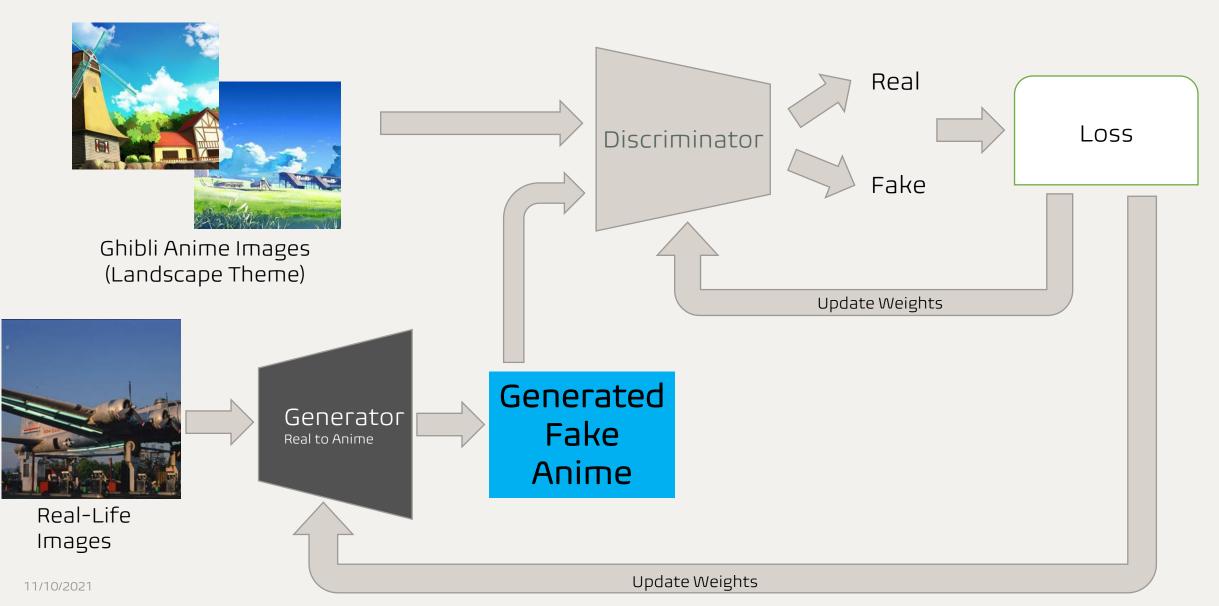








CycleGAN with Curated Theme Anime



CycleGAN with Curated Theme Anime

- Model do better on blue skies and may even fill clear blue skies with clouds
- Less incoherent details in generated images
- CycleGAN does not need paired images,
 but matching themes for input and target
 domains improve performance

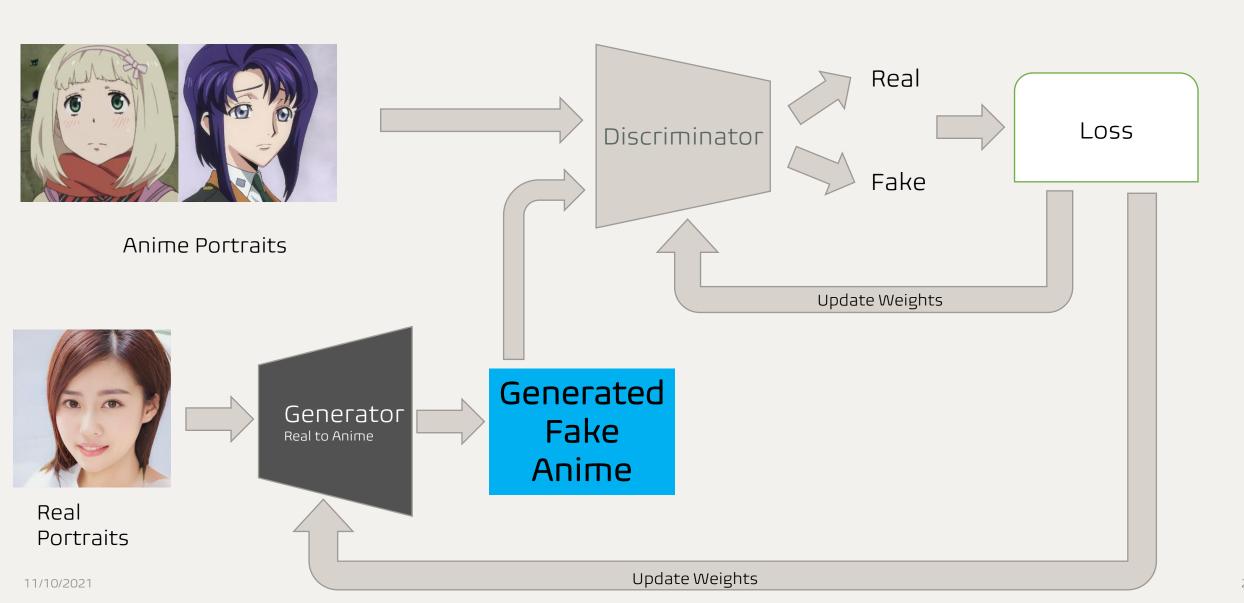








CycleGAN with Anime Portraits



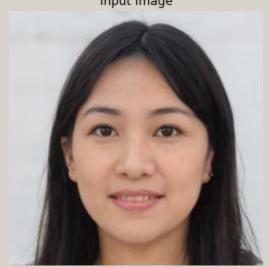
CycleGAN with Anime Portraits

- Model did well with hairstyle but got progressively worse with facial features. Training was stopped early at 60th epoch
- Increase the value of LAMBDA as possible solution so that cyclic consistency loss is given higher importance
- Theoretically guide the model to prioritize the position of the facial features and reduce distortion

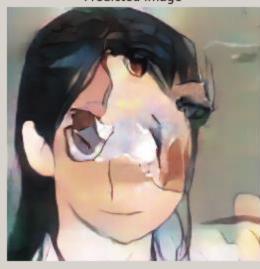




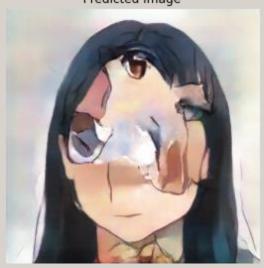
Input Image



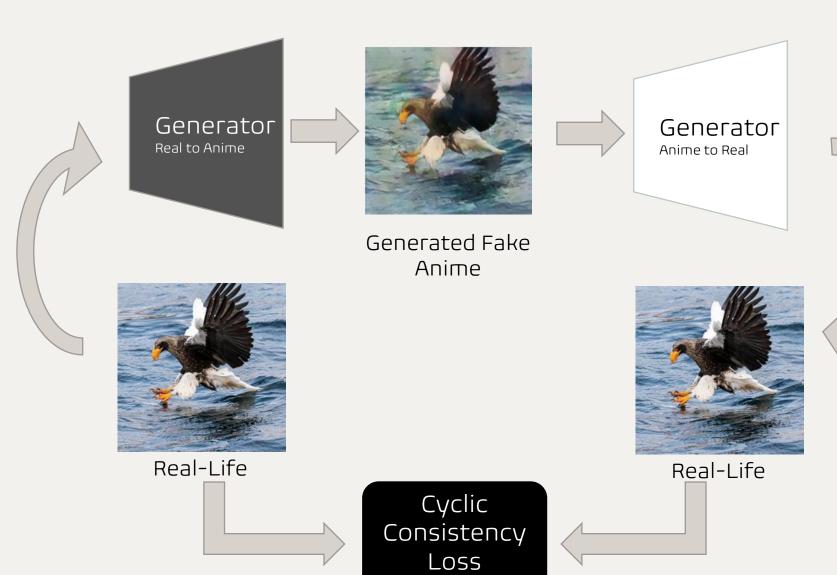
Predicted Image



Predicted Image



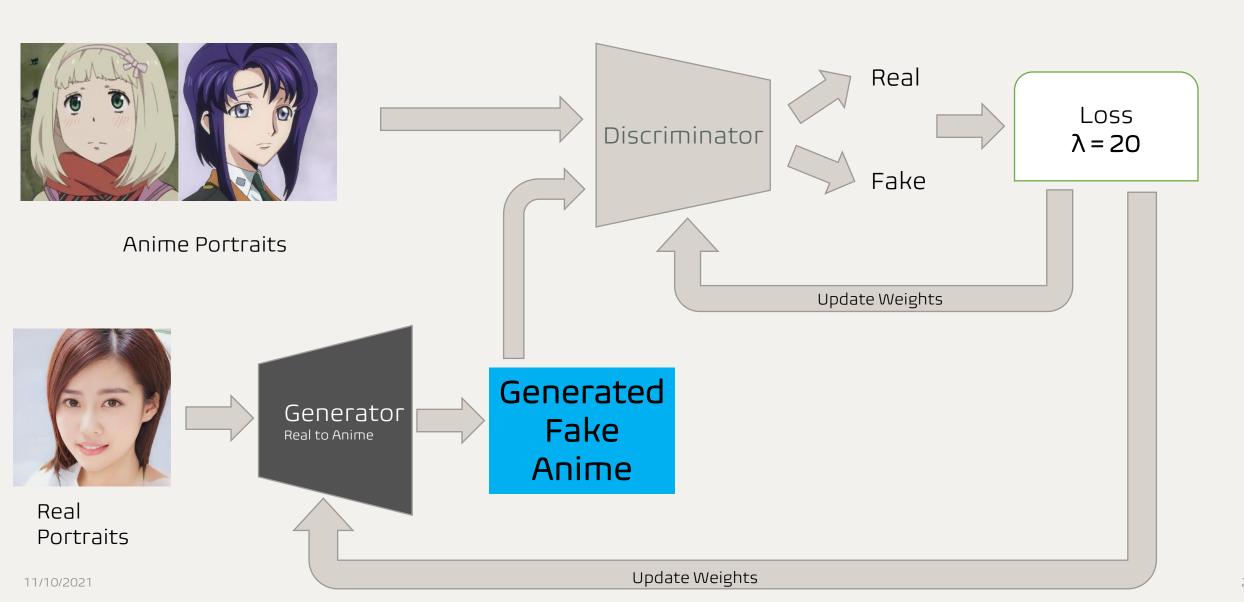
CycleGAN with LAMBDA = 20



Increasing LAMBDA from 10 to 20 gives more importance to cyclic consistency

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

CycleGAN with LAMBDA = 20



CycleGAN with LAMBDA = 20

- Model did badly for facial features right from the beginning.
- Training was ended early at 58th epoch
- Problem may be with the CycleGAN architecture





Input Image



Predicted Image

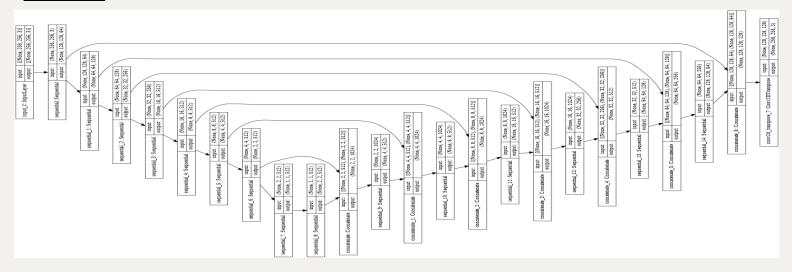


Predicted Image



CycleGAN Generator Architecture

U-Net

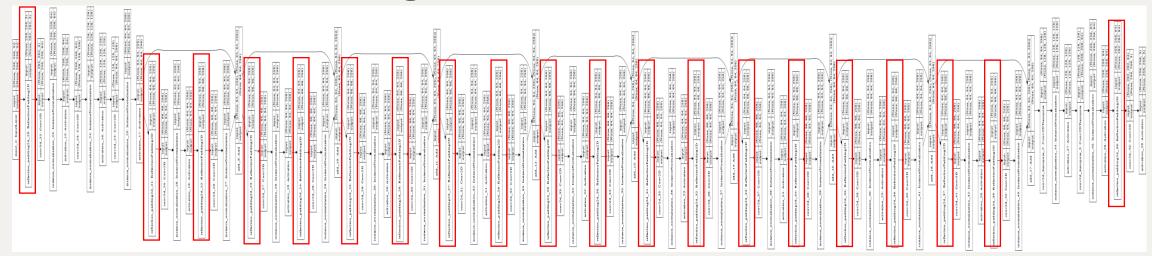


Model Summary

concatenate_4 (Concatenate)	(None,	32,	32,	512)	0	sequential_12[0][0] sequential 2[0][0]
sequential 13 (Seguential	/None		61	120\	590208	concatenate 4[0][0]
		(110116)					
concatenate_5 (Co	Concatenate)	(None,	64,	64,	256)	0	sequential_13[0][0]
							sequential_1[0][0]
sequential_14 (Sequential)	(None,	128	, 128	3, 64)	147648	concatenate_5[0][0]
concatenate_6 (0	Concatenate)	(None,	128	, 128	3, 128	0	sequential_14[0][0]
							sequential[0][0]
conv2d_transpos	e_7 (Conv2DTrans	(None,	256	, 256	3, 3)	3459	concatenate_6[0][0]
Total params: 3							
Trainable param	ns: 30,618,691						
Non-trainable p	arams: 0						

CycleGAN Generator Architecture

ResNet with ReflectionPadding2D



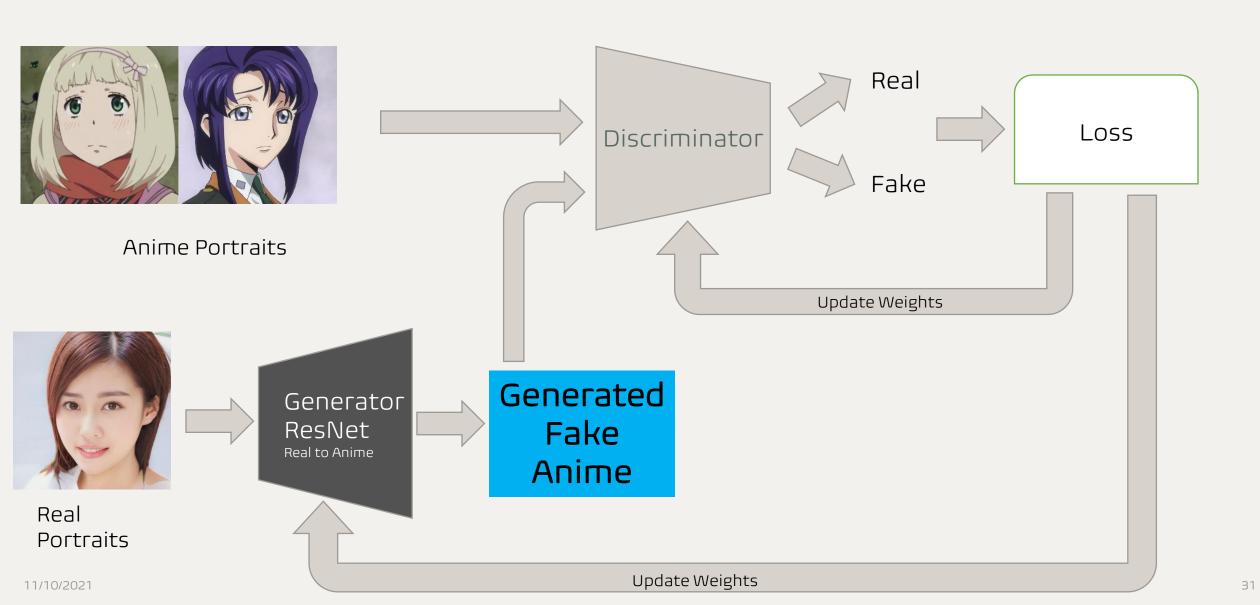
Model Summary

Trainable params: 11,388,675

	ne,	256,	256,	64)	0	instance_normalization_45[0][0]
reflection_padding2d_39 (Reflec (No	one,	262,	262,	64)	0	activation_28[0][0]
conv2d_43 (Conv2D) (No	ne,	256,	256,	3)	9411	reflection_padding2d_39[0][0]
activation_29 (Activation) (No	one,	256,	256,	3)	0	conv2d_43[0][0]

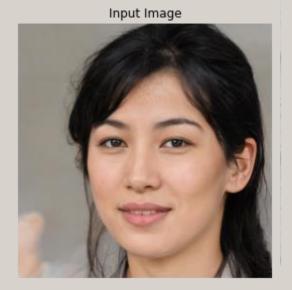
Non-trainable params: 0

CycleGAN with ResNet Generator



CycleGAN with ResNet

- Model did well in facial features position
- Training was ended early at 58th epoch
- Quality is still lacking. Further adjustment of architecture required

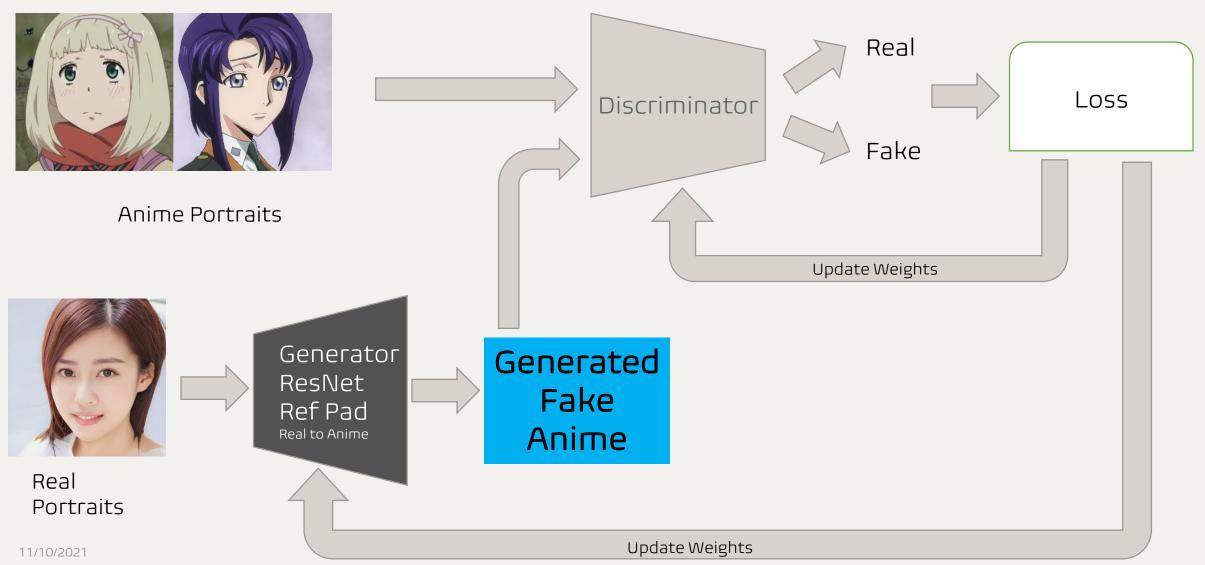






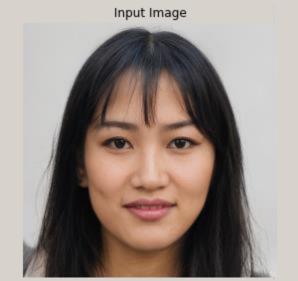


CycleGAN with ResNet Gen and Reflection Padding



CycleGAN with ResNet Gen and Reflection Padding

- Inclusion of ReflectionPadding2D improved quality of image tremendously
- Training was ended early at 100th epoch. Best result at 60th epoch
- Both content of input and anime style was successful transferred







Predicted Image



Predicted Image



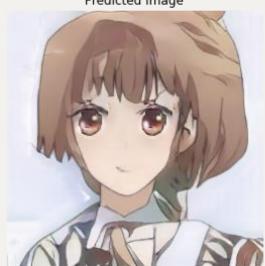
Generated Examples

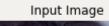




Predicted Image

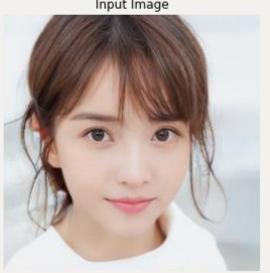
Predicted Image







Input Image



Predicted Image



Predicted Image



Key Takeaways

Landscape and scenery images can be cartoonized using CycleGAN with a U-Net Generator. Requires matching themes and clean real-life and anime datasets

Cartoonization of portraits is sensitive to position of facial features. ResNet may have performed better than U-Net due to fewer parameters and downsampling, which is better for color and style transfer

Cyclic Consistency and the CycleGAN architecture allowed input image content retention without paired data

ReflectionPadding2D helps to keep data distribution of input image intact vs Zero Padding, which may have helped performance



THANK YOU!

