



# Application of GANs for style transfer

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# Introduction

Literature review: Style Transfer using Generative Adversarial Networks.

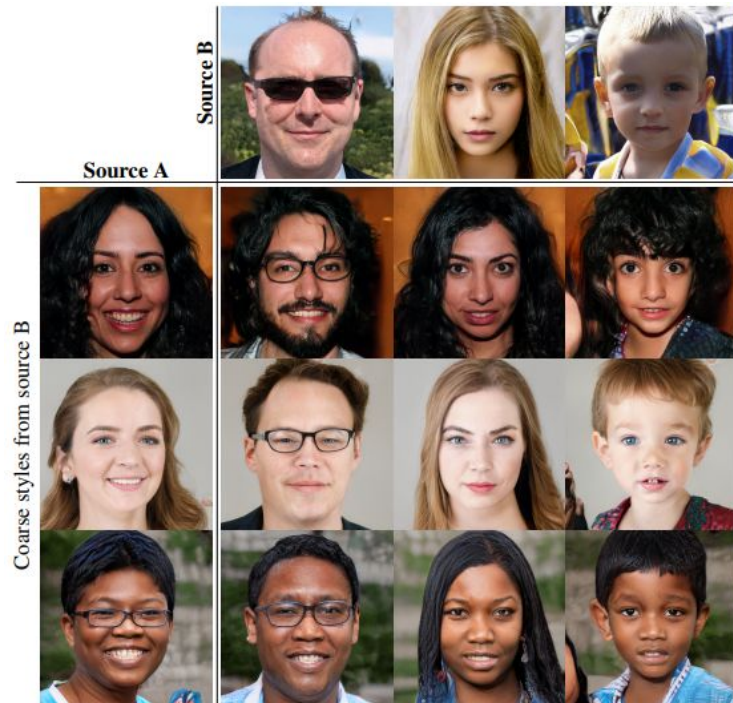
Scope:

- Image style transfer – comes under image-to-image translation
- Discuss multiple ways in which the GANs are being used
- Understand the theory and technical aspects of GANs
- Varied applications of such methods
- Examine the differences between their approaches

# Style-Based Generator GAN

Title: A Style-Based Generator Architecture for Generative Adversarial Networks

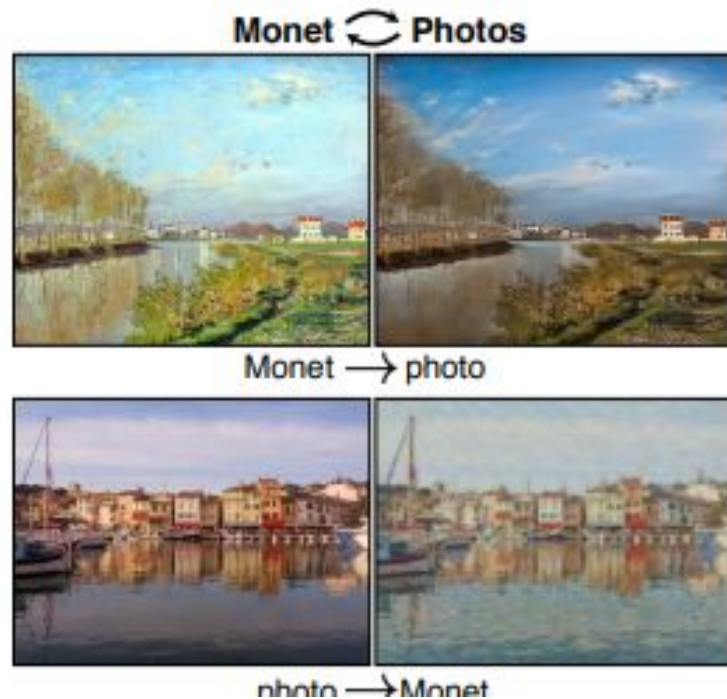
- Alternative architecture to the traditional GAN
- Single image style transfer model
- Generator contains ADAIN blocks



# Cycle GAN

Title: Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks

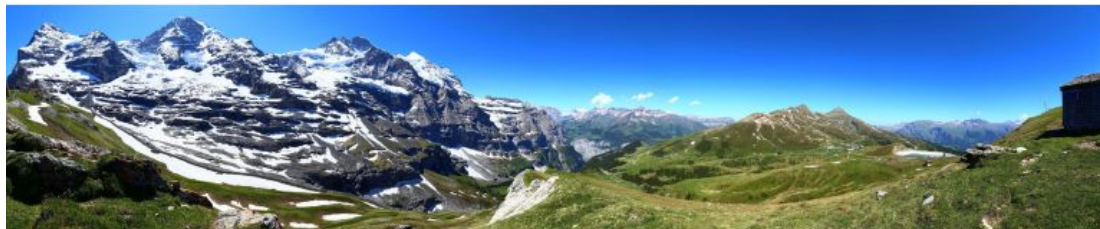
- image-to-image translation
- Generator has multiple residual blocks
- Discriminator has PatchGANs
- Cycle loss



# Domain Transfer GAN

Title: Unpaired High-Resolution and Scalable Style Transfer Using Generative Adversarial Networks

- Image style transfer
- Tackles high memory usage
- Train on small, overlapping image subsamples



# DRB GAN

Title: DRB-GAN: A Dynamic ResBlock Generative Adversarial Network for Artistic Style Transfer

- artistic style transfer - single, collection styles
- Style Encoding Network
- Style Transfer Network
- Discriminative Network

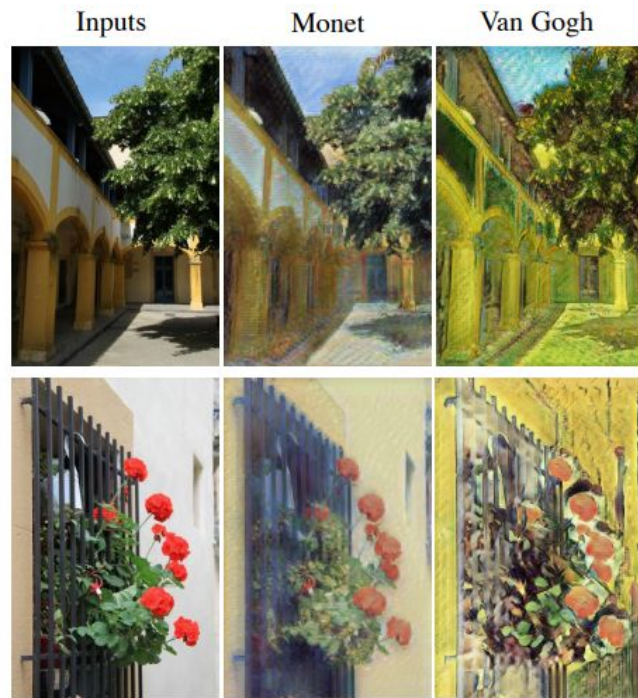


# Gated GAN

Title: Gated-GAN: Adversarial Gated Networks for Multi-Collection Style

Transfer

- Multistyle transfer
- Encoder
- Gated transformer
- Decoder





# Deep learning based GAN

Title: Deep Learning-Based Application of Image Style Transfer

- Improved CycleGAN
- Unet network is replaced with PatchGAN
- Higher quality images





# Unified Generator GAN

Title: A Domain Gap Aware Generative Adversarial Network for Multi-domain Image Translation

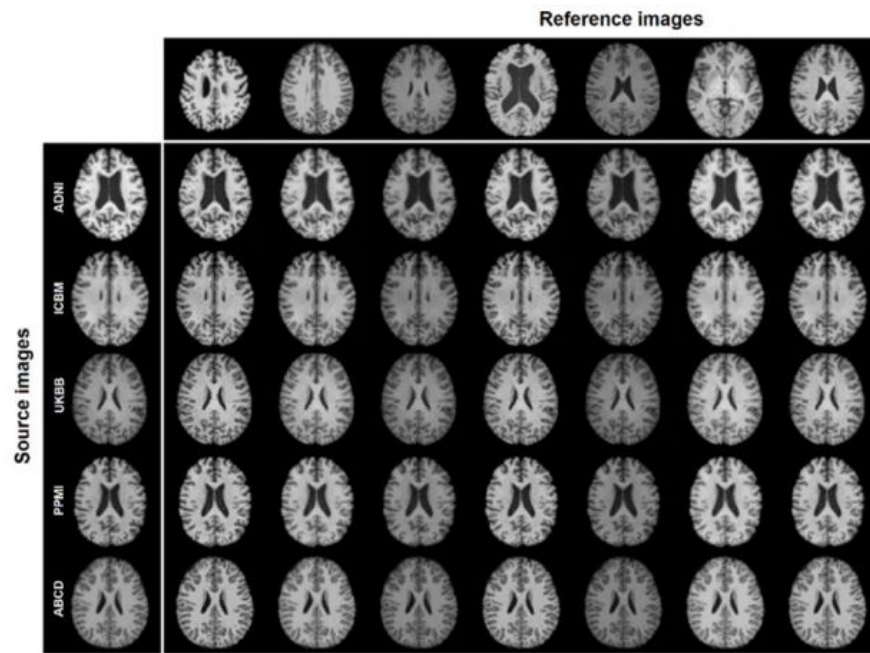
- multi-domain image translation
- UMIT - Unified Generator
- Input-output drawers mechanism



# Style Encoder GAN

Title: Style Transfer Using Generative Adversarial Networks for Multi-Site MRI Harmonization

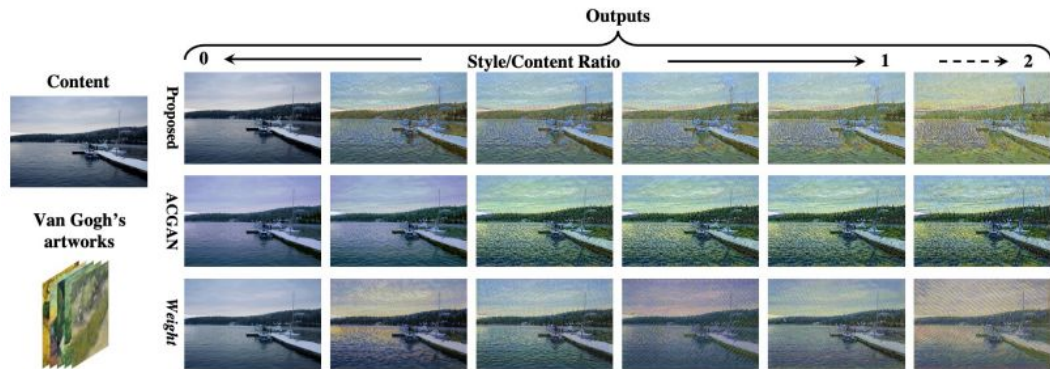
- Single image style transfer
- retrospective harmonization of MRI
- Similar to Style Based Generator GAN



# Style degree controllable GAN

Title: Style Fader Generative Adversarial Networks for Style Degree Controllable Artistic Style Transfer

- Style degree control
- Add extra modules to any existing GAN
- Style Scaling Injection module
- Style Degree Interpretation



# MISS GAN

Title: MISS GAN: A Multi-IlluStrator Style Generative Adversarial Network for image to illustration translation

- image-to-illustration translation model
- Encoder decoder - generator
- Content features loss



# Cartoon GAN

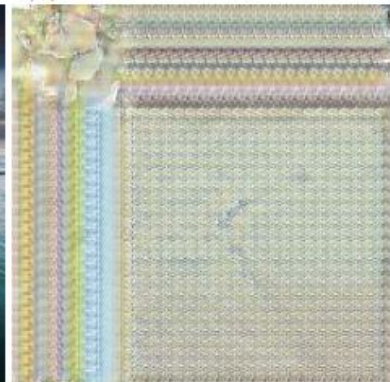
- Paper Title: CartoonGAN: Generative Adversarial Networks for Photo Cartoonization
- transforms real-world captured pictures into cartoonic-style images
- images with clear edges, smooth color shading and simple textures



(a) Input Photo



(b) Without Initialization



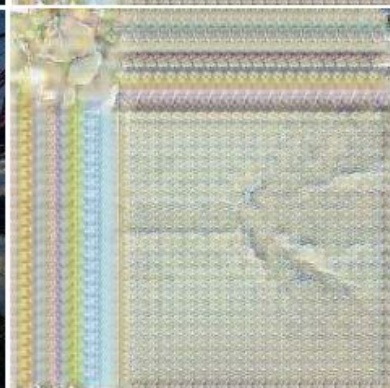
(c) With  $L_2$  loss



(d) Without edge loss



(e) CartoonGAN (ours)



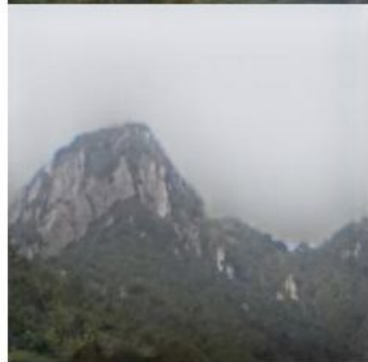
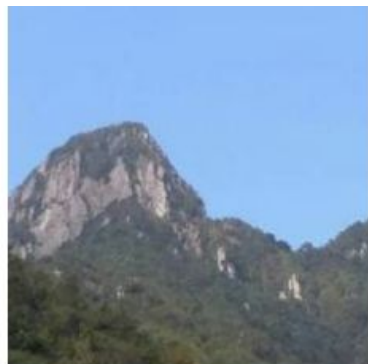


# Weather GAN

- Paper Title: Weather GAN: Multi-Domain Weather Translation Using Generative Adversarial Networks
- transferring weather conditions of an image from one category to another
- a multi-domain weather translation approach based on GAN, called as Weather GAN
- transferring of weather conditions like sunny, cloudy, foggy, rainy and snowy specifically
- weather conditions in the image are determined by various weather-cues, such as cloud, blue sky, wet ground, etc



(a) Sunny  $\rightarrow$  Cloudy



(b) Sunny  $\rightarrow$  Foggy



(c) Sunny  $\rightarrow$  Snowy



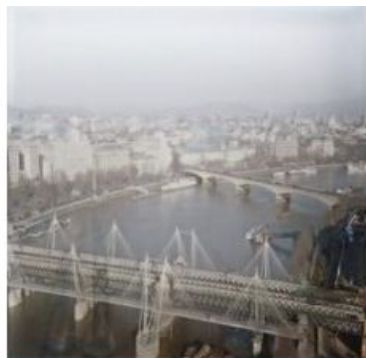
(d) Cloudy  $\rightarrow$  Snowy



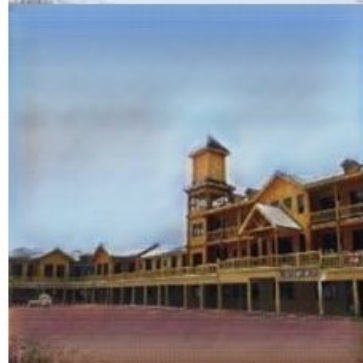
(e) Sunny  $\rightarrow$  Rainy



(f) Cloudy  $\rightarrow$  Sunny



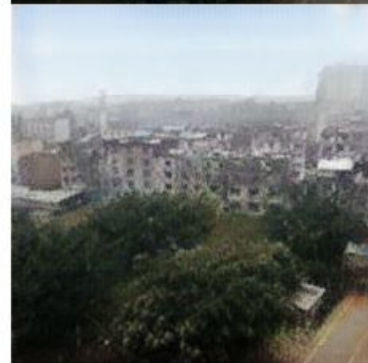
(g) Foggy  $\rightarrow$  Sunny



(h) Snowy  $\rightarrow$  Sunny



(i) Snowy  $\rightarrow$  Cloudy

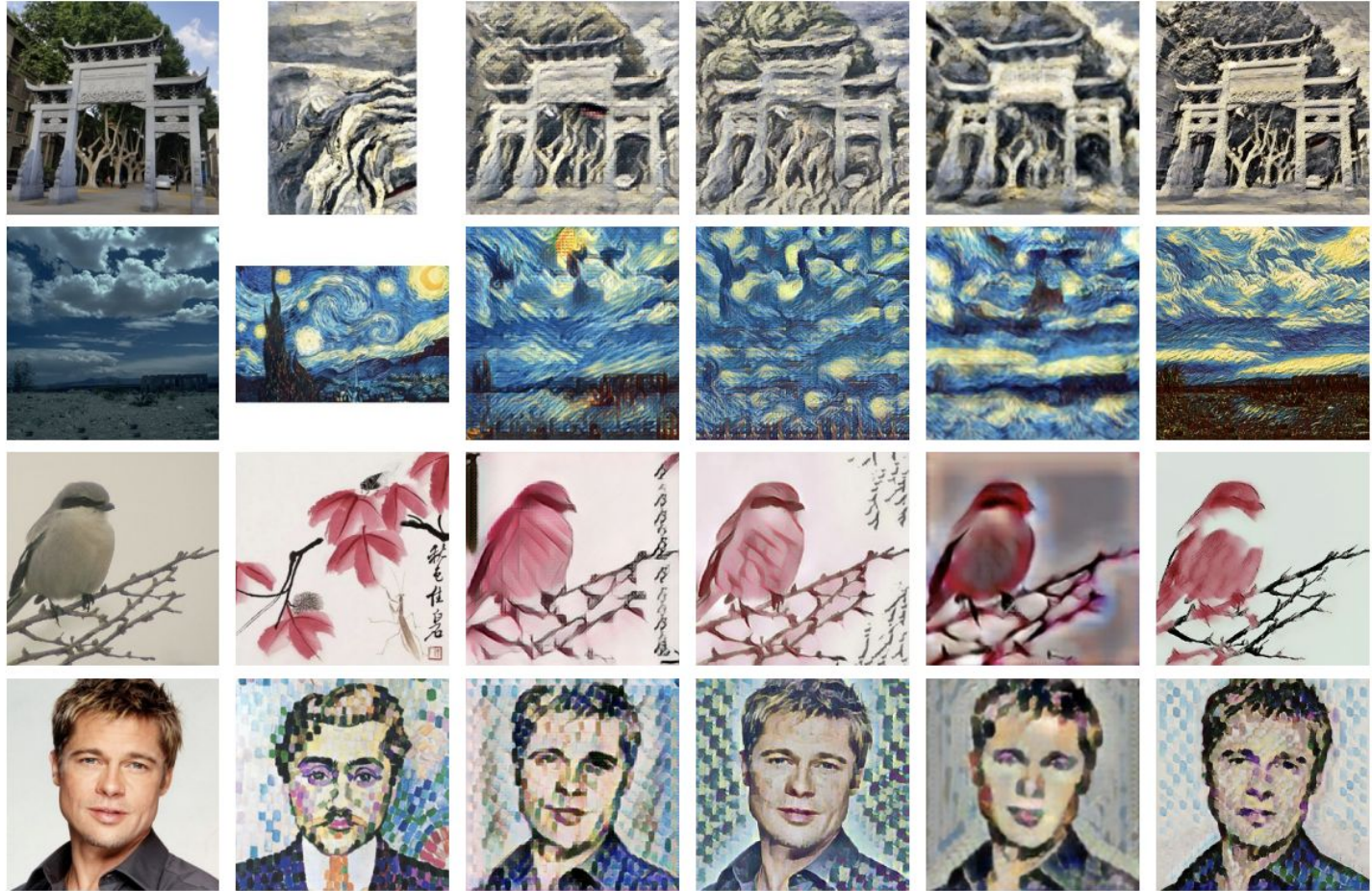


(j) Rainy  $\rightarrow$  Sunny

# P2 GAN

- Paper Title: P2-GAN: EFFICIENT STYLE TRANSFER USING SINGLE STYLE IMAGE
- efficiently learns the stroke style from a single style image
- we use patch permutation to generate multiple training samples of images from the given style image
- simultaneously process patch-wise images and natural images seamlessly





(a) Content (b) Style (c) JohnsonNet (d) TextureNetIN (e) MGAN (f) Ours

# Auxiliary Classifier (AC) GAN

- Paper Title: Style Transfer for Anime Sketches with Enhanced Residual U-net and Auxiliary Classifier GAN
- not just randomly colorize sketch lines as outputs, they also do specific style transfer
- applies the style to the grayscale sketch with auxiliary classifier generative adversarial network (AC-GAN)





# CLIP Styler

- Paper Title: CLIPstyler: Image Style Transfer with a Single Text Condition
- enables a style transfer 'without' a style image, but only with a text description of the desired style
- modulation of the style of content images only with a single text condition
- successful image style transfer with realistic textures that reflect semantic query texts

Content Image

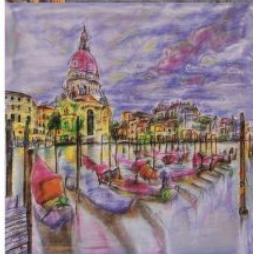
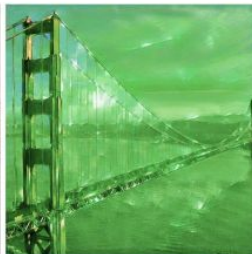
“Mosaic”

“A sketch with  
crayon”

“White wool”

“Green crystal”

“A graffiti style  
painting”



# Aug GAN

- Paper Title: GAN-Based Day-to-Night Image Style Transfer for Nighttime Vehicle Detection
- transform on-road driving images to a desired domain while image-objects would be well preserved
- image-to-image translation network across different domains
- domain adaptation capability of a vehicle detector
- significant performance gain in the difficult day-to-night case in terms of vehicle detection
- generate more visually plausible images compared to competing methods





# Conditional GAN

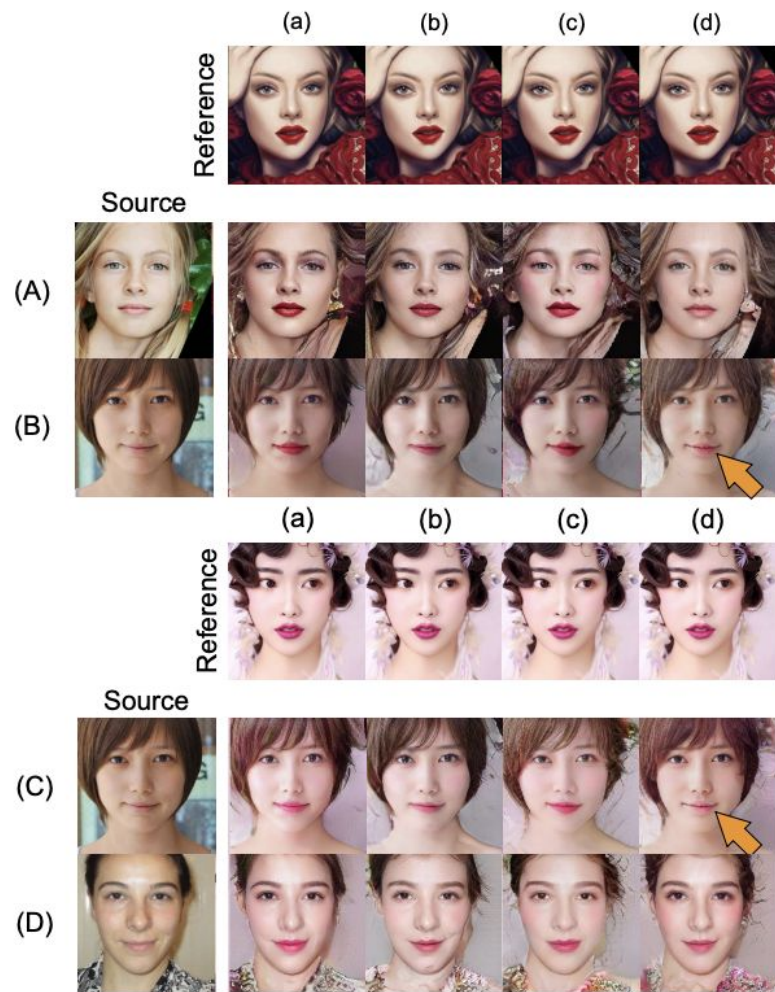
- Paper Title: Image Generation and Style Transfer Using Conditional Generative Adversarial Networks
- testing performance on a combination of image datasets, using the same type of input-output mapping
- a model can transfer characteristics such as style and design from one dataset to another
- conditional GAN model handles multiple conditional inputs, taking both the input image map and a class label



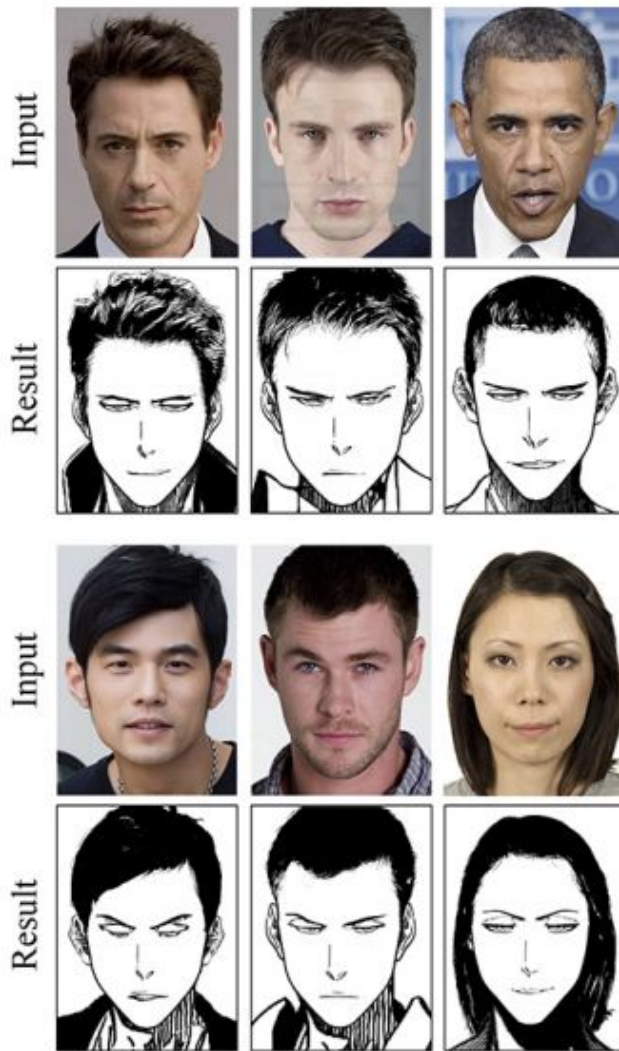
Input	Output for Label “Leather”	Default Output (no label)	Target
			
			
			
			
			
			

# SL GAN

- Paper Title: SLGAN: Style- and Latent-guided Generative Adversarial Network for Desirable Makeup Transfer and Removal
- used to apply makeup to photos of the human face
- factors taken into consideration include (1) facial components, (2) interactive color adjustments, (3) makeup variations, (4) robustness to poses and expressions, and the (5) use of multiple reference images, all these 5 features simultaneously
- SLGAN is better than other comparable state-of-the-art methods



# Manga GAN



# RPD GAN



# Conclusion

- Style transfer using Generative Adversarial Networks (GANs) has become an increasingly popular research topic in the deep learning community.
- Through the use of GANs, it is possible to create new images that combine the content of one image with the style of another.
- Our survey paper has reviewed various style transfer GAN architectures, including CycleGAN, CartoonGAN, DRB-GAN, MangaGAN and many more.
- We have also discussed the datasets used for training style transfer GAN models, which are typically large collections of diverse images.