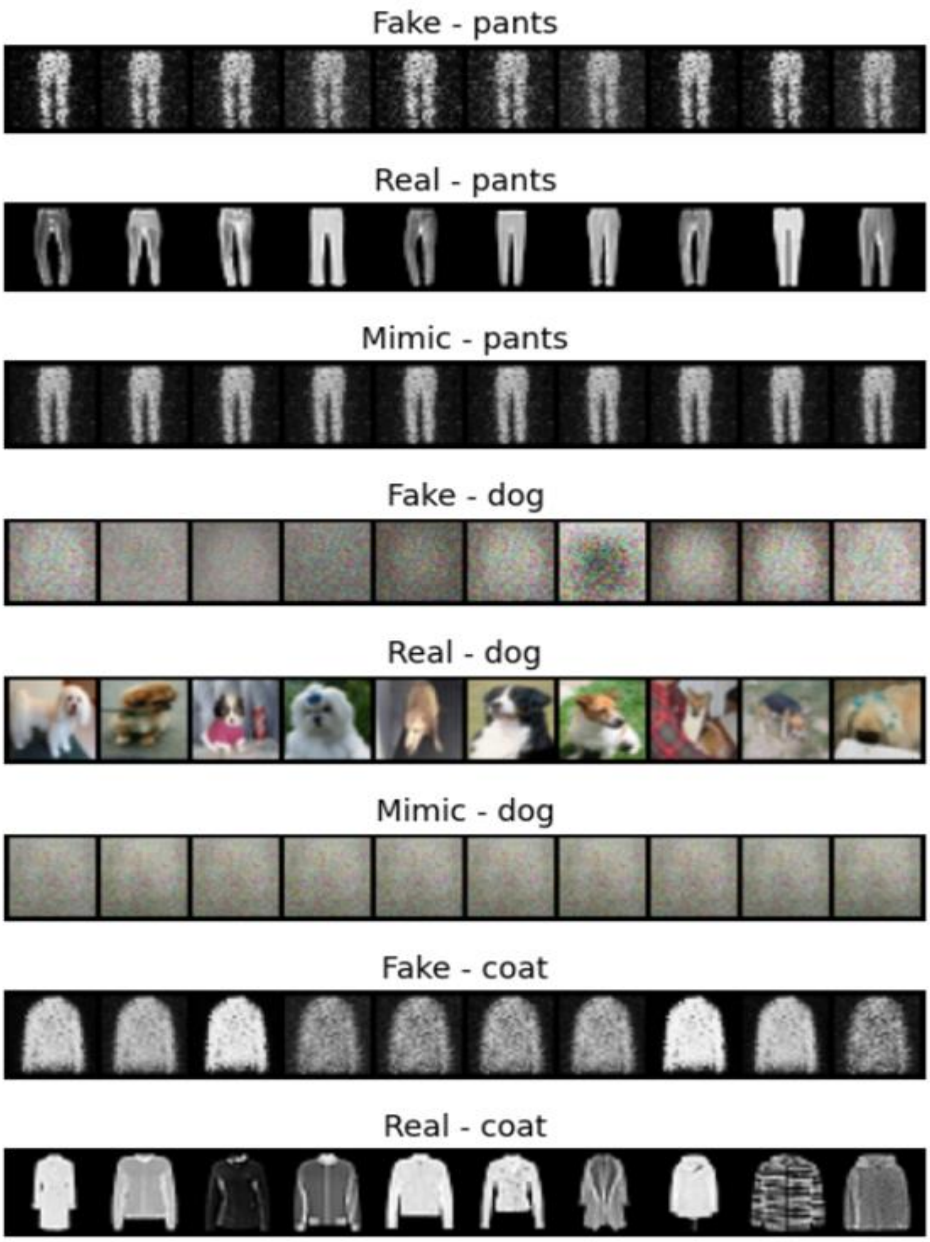
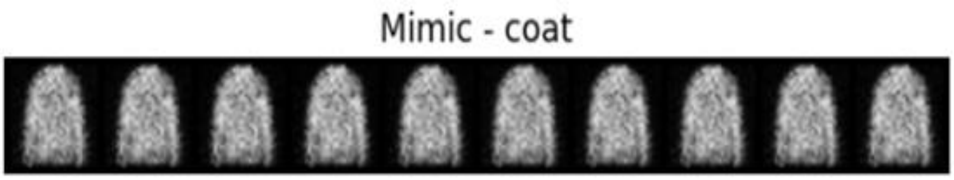
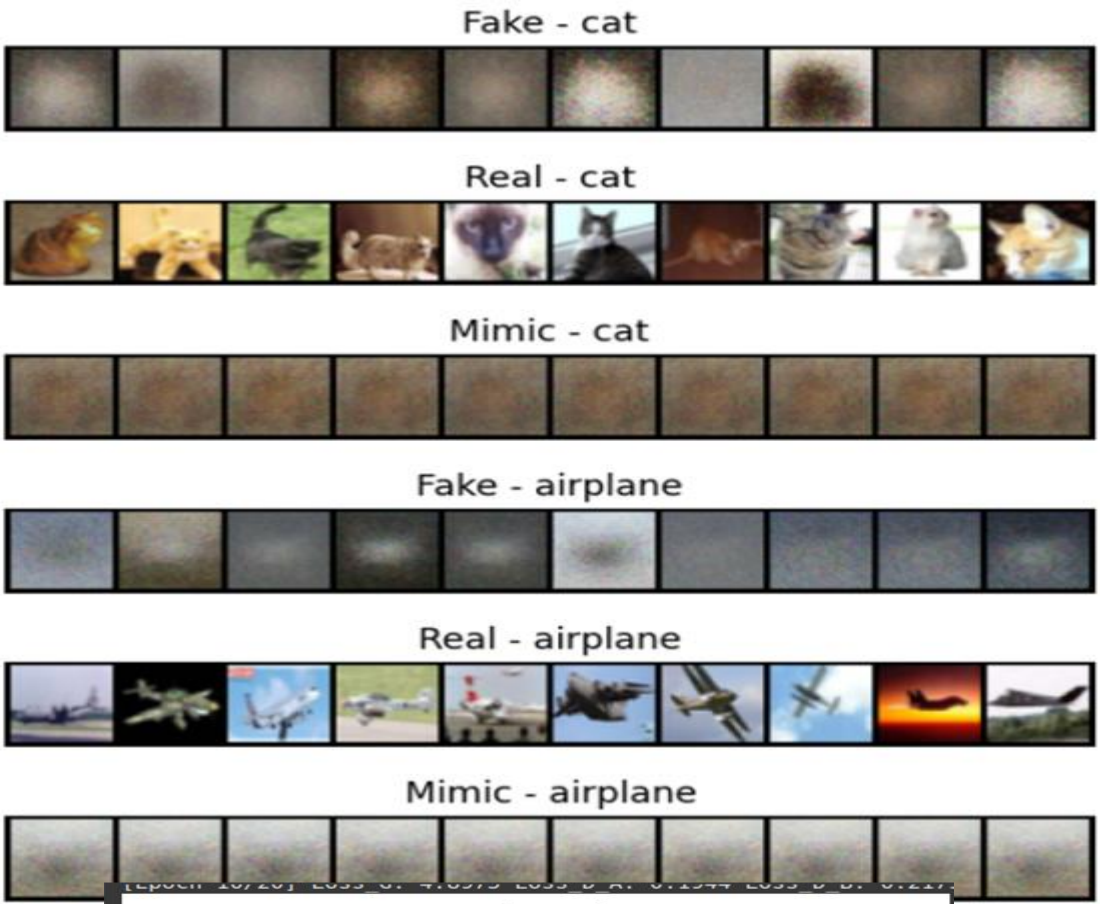
Lab 9

Results:

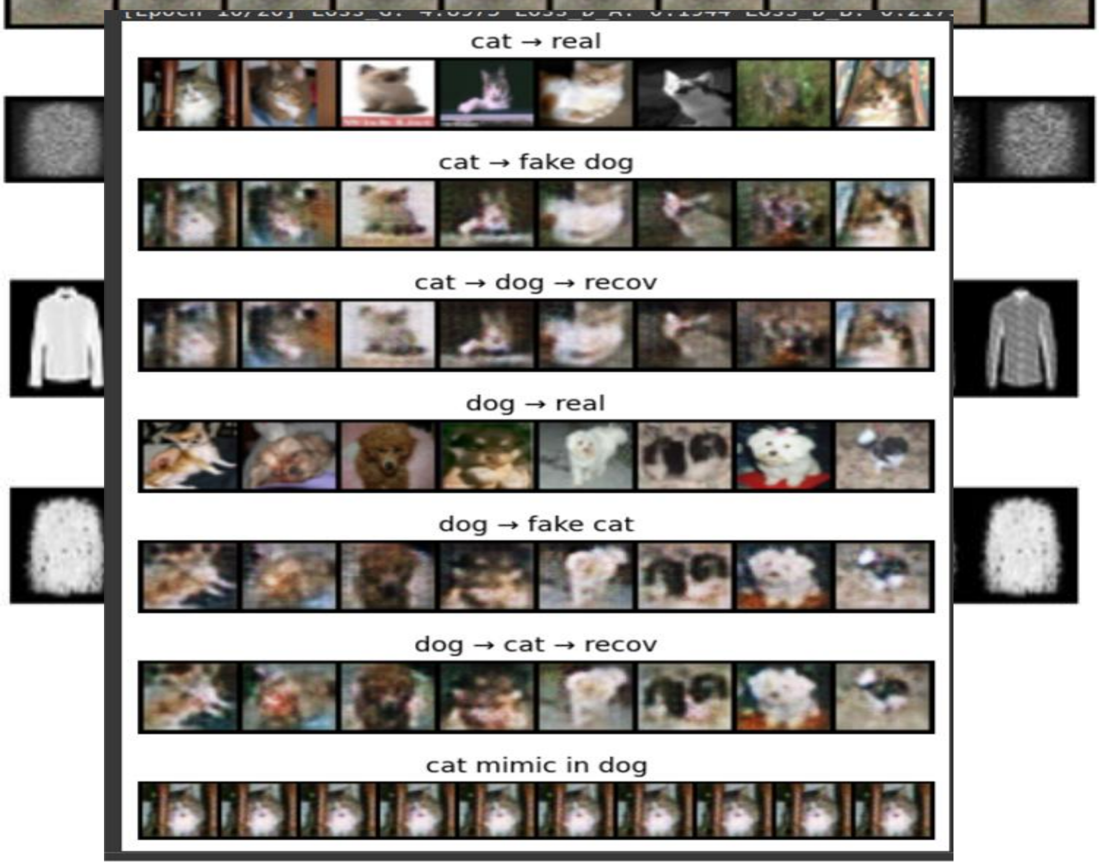
1. Gan

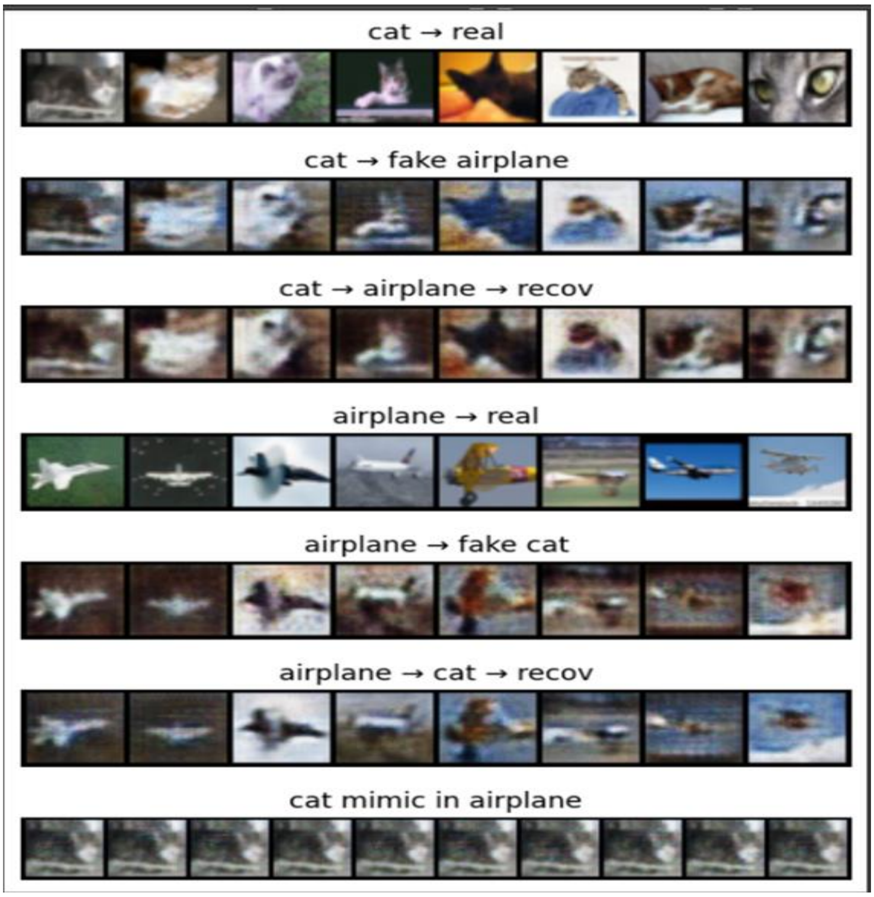




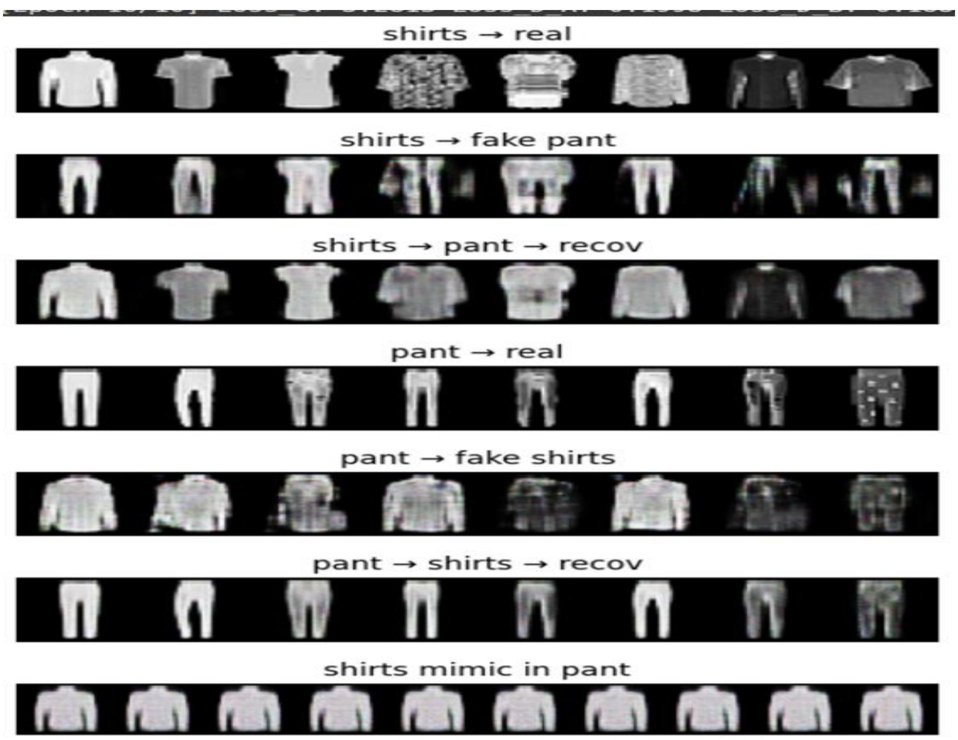

Fake - cat
Real - cat
Mimic - cat
Fake - airplane
Real - airplane
Mimic - airplane

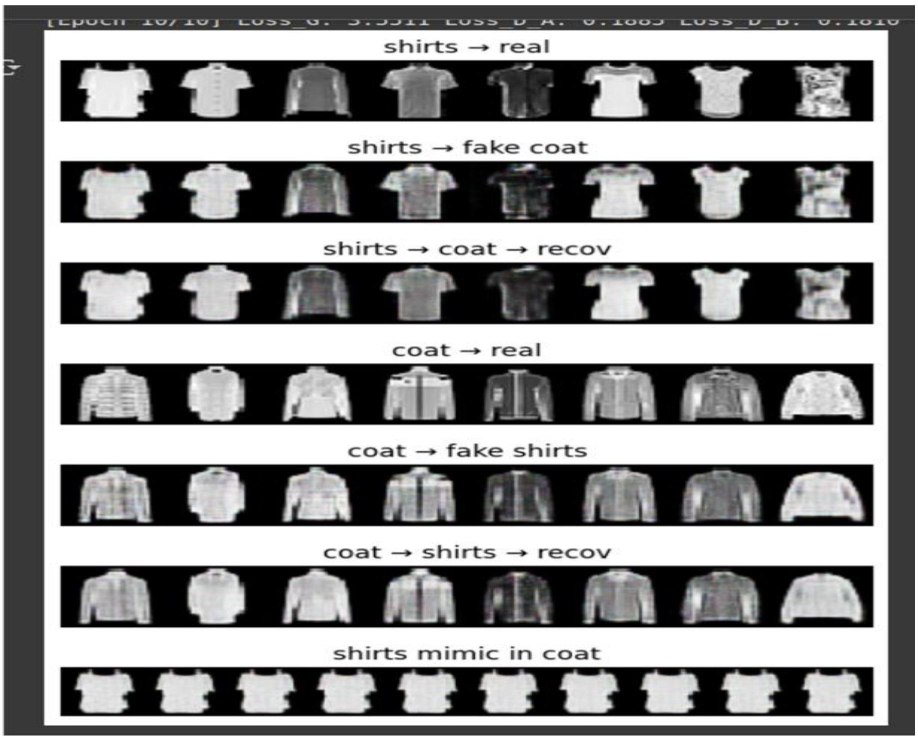
2.cycle Gan

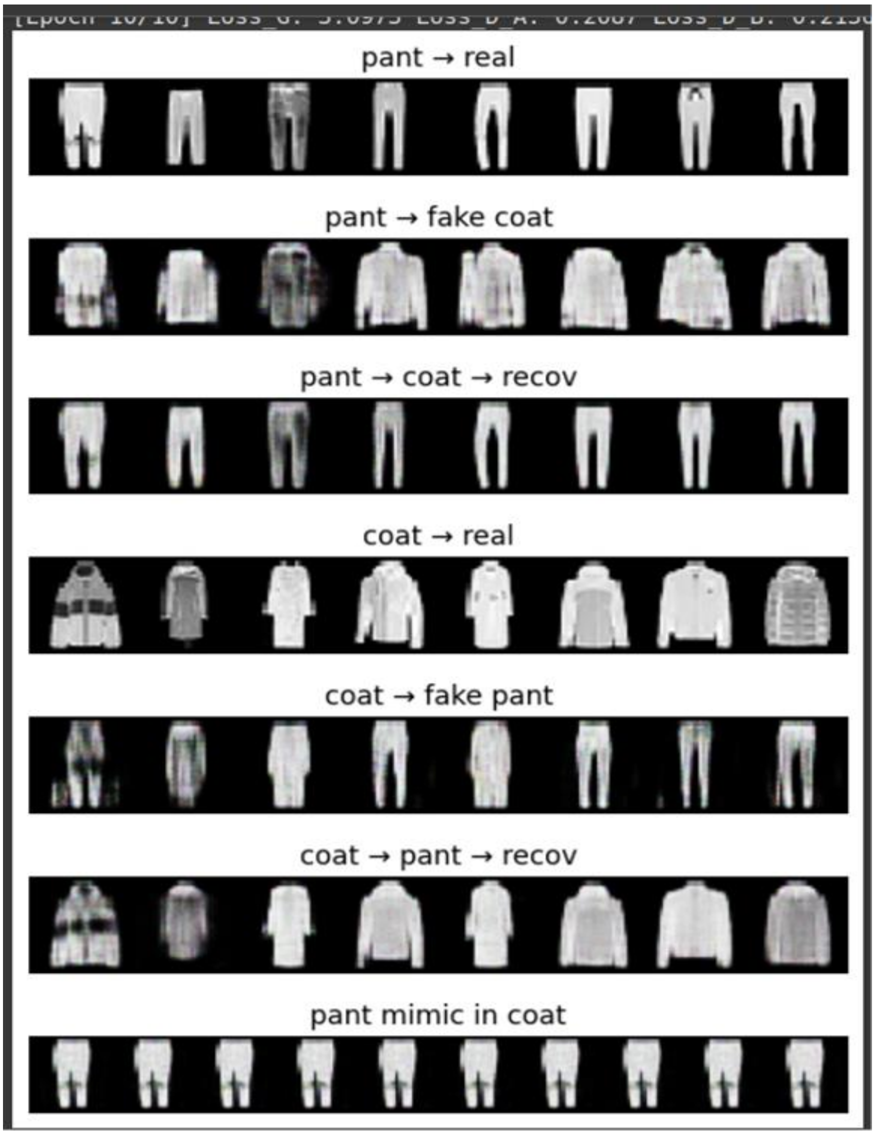

cat → real
cat → fake dog
cat → dog → recov
dog → real
dog → fake cat
dog → cat → recov
cat mimic in dog

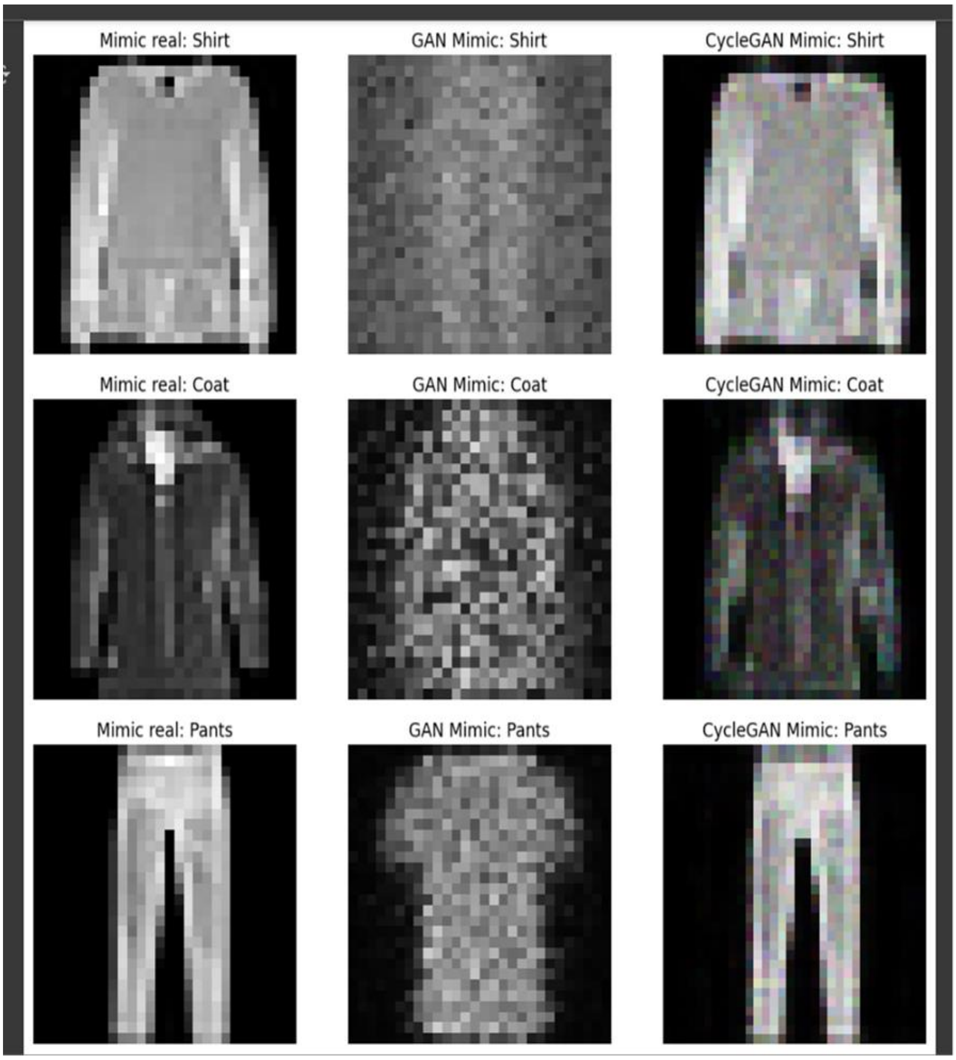

cat → real
cat → fake airplane
cat → airplane → recov
airplane → real
airplane → fake cat
airplane → cat → recov
cat mimic in airplane


airplane → dog → recov
dog → real
dog → fake airplane
dog → airplane → recov
airplane mimic in dog


shirts → real
shirts → fake pant
shirts → pant → recov
pant → real
pant → fake shirts
pant → shirts → recov
shirts mimic in pant


shirts → real
shirts → fake coat
shirts → coat → recov
coat → real
coat → fake shirts
coat → shirts → recov
shirts mimic in coat


pant → real
pant → fake coat
pant → coat → recov
coat → real
coat → fake pant
coat → pant → recov
pant mimic in coat



QA:

1. (7%) Which model generated more realistic or varied results — GAN or CycleGAN?
CycleGAN generally produces more realistic and stylistically consistent images, especially in class-to-class transfer tasks.

When I compared examples like shirt → coat or cat → dog, CycleGAN produced structurally coherent, tonal images, while GAN blurred between categories and often generated images lacking detail.
The training method of CycleGAN includes cycle consistency loss, so it is better at preserving the structural information of the input image.

Here is a visual comparison:
The images generated by GAN are sometimes repetitive, blurry, and have low class recognition.

CycleGAN images are more stable, retain the style of the original content, and transfer the target appearance.

2. (7%) How did style mimic perform across both models?
CycleGAN mimic effect is significantly better than GAN.

CycleGAN's mimic results can usually better preserve the structure and posture of the original image. For example, in the task of dog mimic cat, the overall shape and tone are close to the original image.

GAN mimic images often fail to converge to a stable appearance. Even after 200 steps of optimization, they are still blurry and lack obvious target features.

Observed limitations and artifacts:
GAN mimic suffers from mode collapse: different inputs generate similar results.
CycleGAN mimic sometimes has unnatural background colors or details, but the main shape is relatively stable.

3. (6%) How would you improve the quality of generated results?
Improve the architecture: Use the U-Net structure (especially the generator) to enhance the ability to generate image details; or introduce the attention module to improve the style correspondence of important areas.
Adjust the loss function: Try Least Squares GAN (LSGAN) or Wasserstein GAN with Gradient Penalty (WGAN-GP) to stabilize training and avoid mode collapse.

Regularization techniques:
Added spectral normalization to control discriminator overshoot.
Use instance normalization to increase style consistency.

Training tips:
Appropriate use of label smoothing or one-sided label flipping can increase stability.
Progressive training to increase resolution also helps improve the final image quality.

Data processing: Higher resolution training, more accurate data labels, and the use of image enhancements such as color jittering and flipping help generate sample diversity.