Real-to-Cartoon Image Translation with CycleGAN

AML 2025 Group 19
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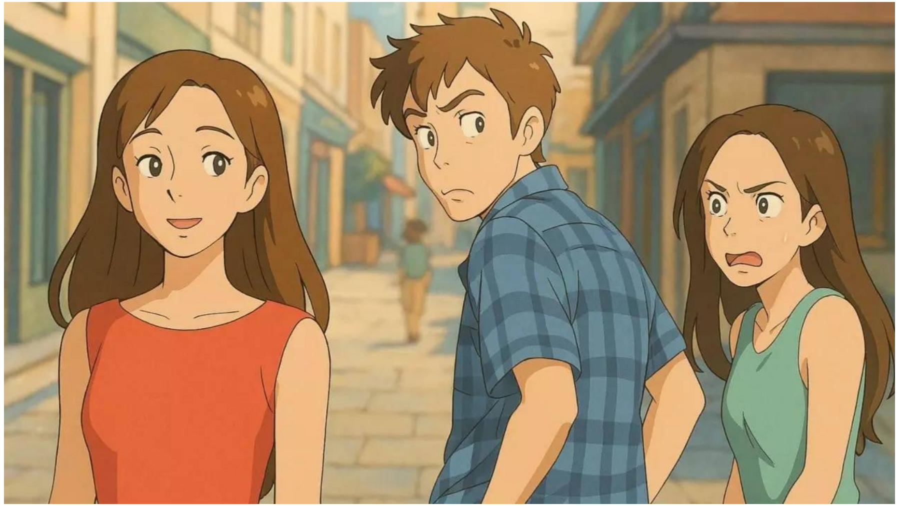
Motivation & Use Case

Automatic cartoonization of photos is useful for:

- Creative industries (animation, graphic design)
- Social media filters
- Identity anonymization



Manual cartoonization is time-consuming.

Can we learn the mapping from unpaired photo-cartoon datasets?

Problem Statement

Goal: Convert real photos into a cartoon-like style using unpaired datasets.

Challenges:

- No pixel-wise supervision (unpaired domains)
- Avoid mode collapse and preserve content structure

Related Work

- **CycleGAN (Zhu et al. 2017):** unpaired image-to-image translation using cycle-consistency loss.
- **U-GAT-IT (Kim et al. 2020):** attention-guided translation with stronger stylization.
- **SwinIR (Liang et al. 2021):** transformer-based backbone for image restoration – we test its use as a generator backbone.

Dataset

Source: Web-crawled photos and cartoons.

Preprocessing:

- Resized to 256×256
- Colors normalized to match the model

Domains:

- Real: 2667 human photographs from Kaggle dataset

  https://www.kaggle.com/datasets/tapakah68/supervisely-filtered-segmentation-person-dataset

- Cartoon: 412 frames from the soviet cartoon “Трое из Простоквашино” 1978

Evaluation Metrics

- **FID Score** (Fréchet Inception Distance): lower is better.
- **Qualitative Inspection:** Does the output resemble hand-drawn cartoons?
- **Training Stability:** Monitor losses (G, D, cycle, identity).

Our Approach

Start from statistical baseline, then modify generator with:

- ChainGAN approach
- SwinIR, UNet and ResNet backbones
- Test additional losses

Statistical Baseline: Color Transfer

Approach: Match color statistics (mean, std) between real photos and cartoon images

- **train_B** — cartoon-style images
- For each of the 3 channels (R, G, B), computed:
  mean_B, **std_B**

- Did the same for **train_A** (real photos):
  mean_A, **std_A**

- Transformed each image from **test_A** using the formula:
- FID ≈ 300 and 368 without the transfer

$$\frac{pixel_{old} - mean_{old}}{std_{old}} \cdot std_{new} + mean_{new}$$

SwinIR: A Transformer Backbone for Image Restoration

🧱 **Architecture Highlights:**

- Hierarchical **Swin Transformer blocks** with **shifted window attention**
- Captures local and non-local context efficiently
- Better than CNNs in fidelity, **but costly to train**

⚠️ **Practical Limitation in Our Case:**

- **Training time was a major bottleneck**
  - Training even **5–10 epochs** took days
  - Needed **100+ epochs** to converge fully
- Transformer-based backbones like SwinIR offer quality gains, but:

Not viable under time/budget constraints in our project

Before

After

After

ResNet9: Fast and Simple Backbone

- **ResNet9** is a compact ResNet variant:
  - 9 convolutional layers
  - Residual connections to maintain gradient flow
  - Popular for lightweight GAN applications

- For our project it is:
  - **Much faster** training than transformers
  - **Stable convergence** in early epochs
  - Low memory usage and decent GPU utilization
  - Easy to plug into CycleGAN-style architecture

    - FID ≈ 238

Before

U-Net + Improved Loss Performs Better

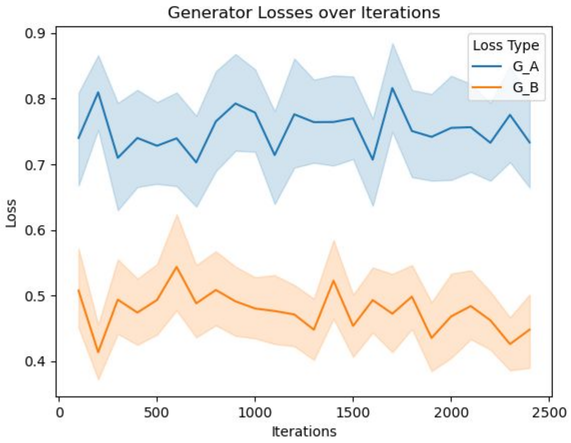
- We replaced the ResNet generator with a **U-Net** architecture.
- U-Net's skip connections help preserve spatial details, improving output sharpness.
- Combined with a tuned loss: **Cycle + Identity + GAN + slight Perceptual Loss**.
- Results are:
  - Visually more coherent.
  - **FID score improved** over ResNet9 and statistical baseline (FID ≈ 200).
- U-Net proved to be **more sample-efficient**, achieving decent quality in fewer epochs.

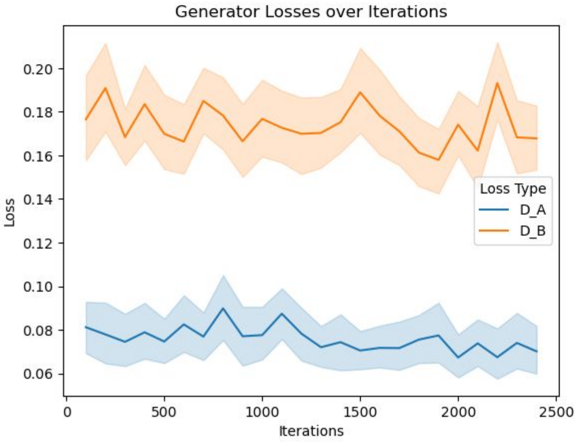
Results

FID: **200**

Outputs show consistent coloring, but:

- Style is not always “cartoonish”
- Shapes and expressions sometimes distorted





We did not reach OpenAI Ghibli quality

But maybe the real style translation was the friends we made along the way

Conclusion & Future Work

CycleGAN with tuned losses and backbones produces images with some degree of style-transfer.

FID still high → needs better domain-specific loss or attention mechanisms.

Acknowledgements & Q&A

- Thanks to the AML2025 TAs Deborah Noemie Jakobi, David Robert Reich, and Lena Jäger.

- Questions?