Rainy Image Restoration

Eduardo Turriza
Albert Jané
Ana Cereto

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1. Motivation

Motivation

- Image restoration research mainly focuses on noise, blur, and low resolution
- Rain and other natural phenomena have received less attention
- Rain degrades images with streaks, occlusions, and reduced contrast
- Affects everyday photography and applications like smartphones, surveillance, and autonomous systems
- Insights can generalize to other water-related scenarios (e.g., splashes, underwater photos)

2. Background

Conditional GAN

The key innovation in cGANs lies in providing both the generator and discriminator with additional contextual information in the form of labels or conditions [1]

Modification in the generator and discriminator:

- It modifies the generator to produce data conditioned on a label
- It modifies the discriminator to verify both authenticity and label consistency

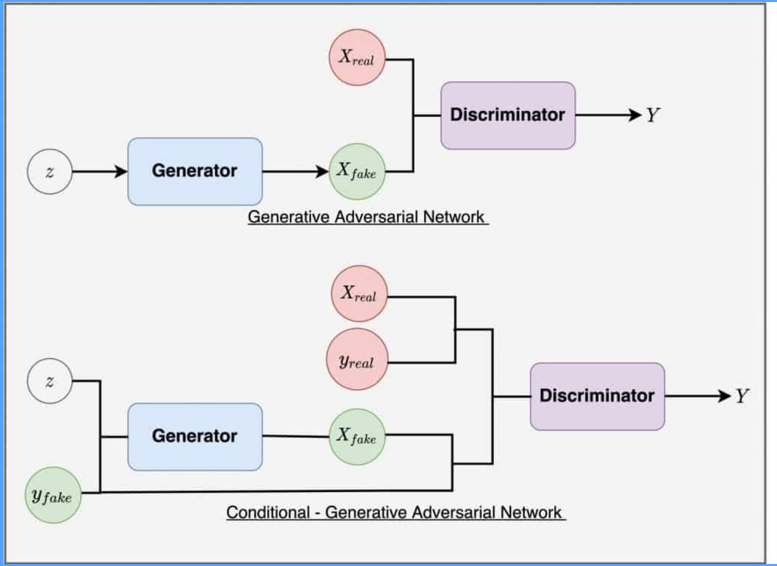

Fig1. Diagram of a Conditional GAN.

Pix2Pix

- Conditional image-to-image translation that uses a conditional GAN.
- U-Net architecture, allows to copy detail through skip connections.
- PatchGAN discriminator, judges if each part of the image looks real.
- Trained with paired data

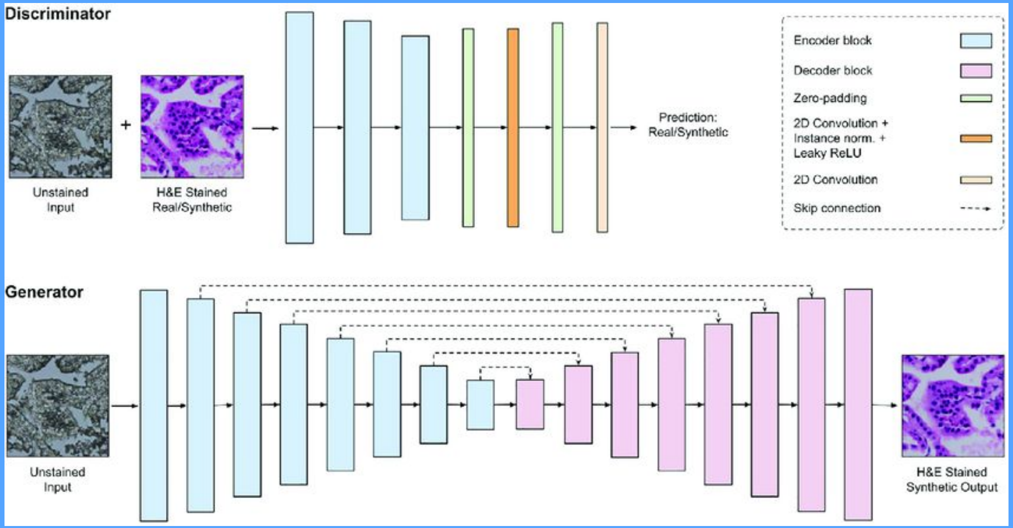

Fig2. Diagram of a Pix2Pix model

3. Dataset

Raindrop dataset

- 1,119 image pairs: same scene, one with raindrops, one clean (ground truth)
- Captured using two identical glass panes: one clean, one sprayed with water
- Split:
  - Train: 860 pairs **(≈ 77%)**
  - Test A: 57 pairs **(≈ 5%)**
  - Test B: 202 pairs **(≈ 18%)**

Fig.3 3 Sample pairs of images from the raindrop dataset

4. Methodology & Results

1. Conditional GAN

Loss function: BCELoss

Hyperparameters:

- 128 latent dimensions
- 32 base channels
- 0.001 learning rate
- Batch size: 8
- Epochs: 20
- Optimizer: Adam

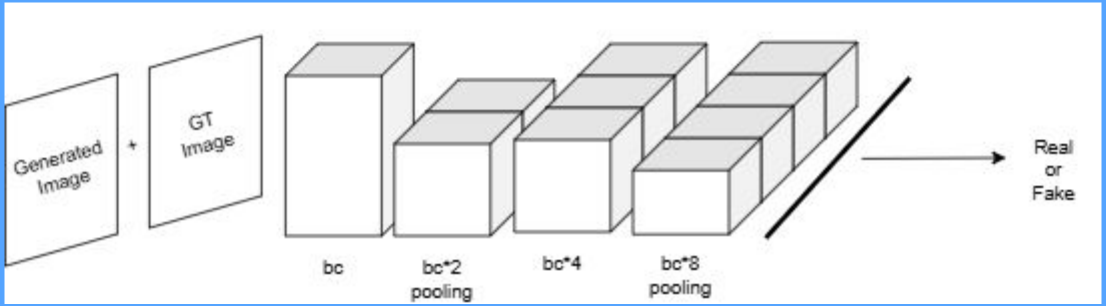

Fig.4 Discriminator

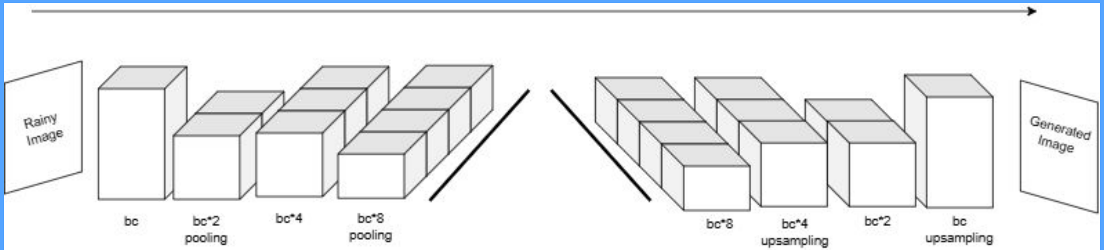

Fig.5 Generator

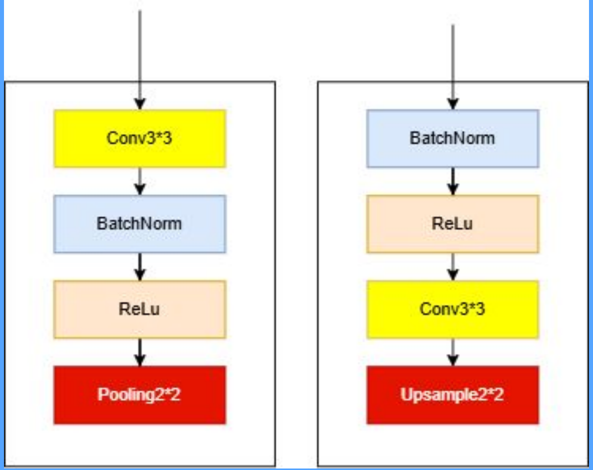

Fig.6 Encoder and decoder blocks

Results

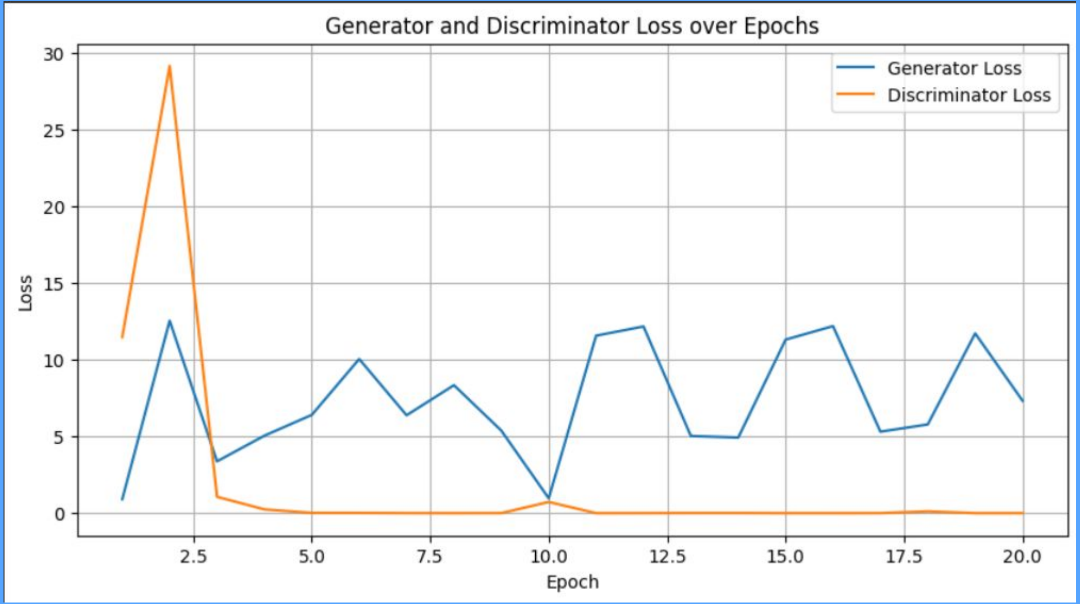

Fig.7 Generator and discriminator loss

Rainy image **Generated Image (clean)**

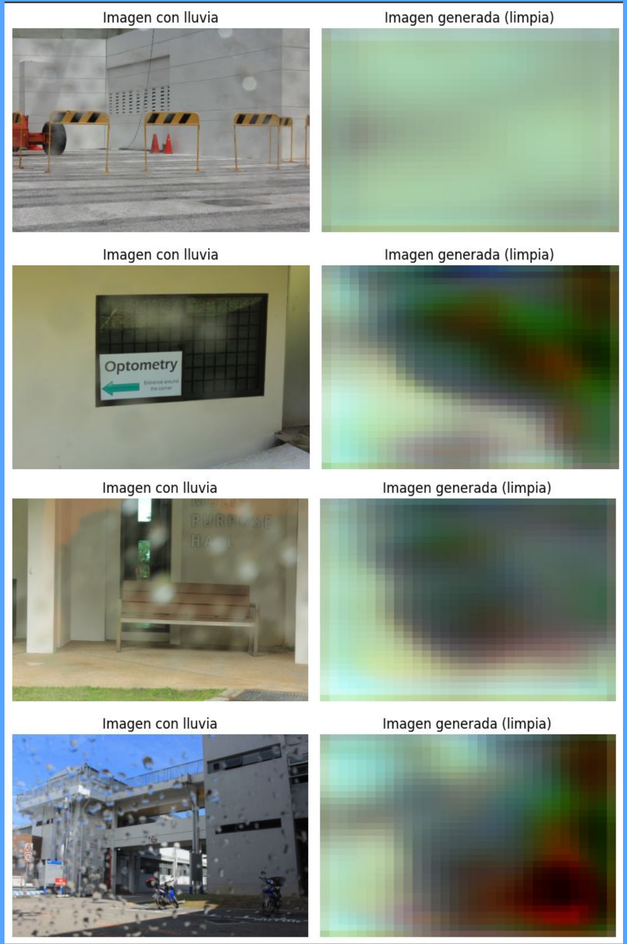

Fig.8 Image results

2. Pix2Pix

Loss functions:

- BCEWithLogitsLoss
- L1 Loss: Difference between generated image and real image

Hyperparameters:

- 128 latent dimensions
- 32 base channels
- Learning rate: 0.0002
- Batch size: 8
- Epochs: 50
- Optimizer: Adam

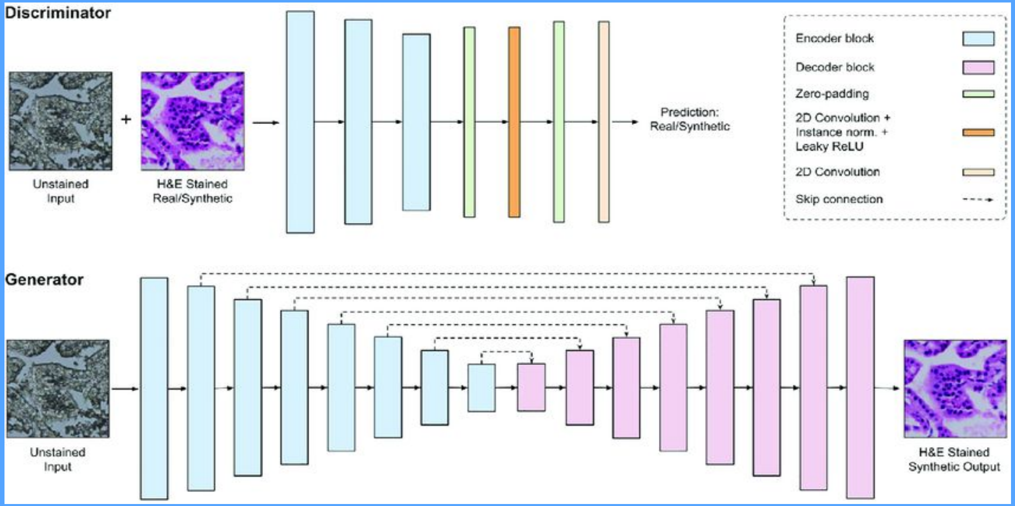

Fig 1. Diagram of a Pix2pix model.

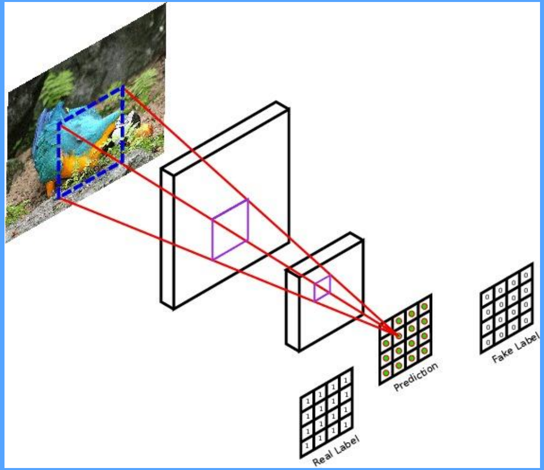

Fig 9. Representation of how PatchAN work.

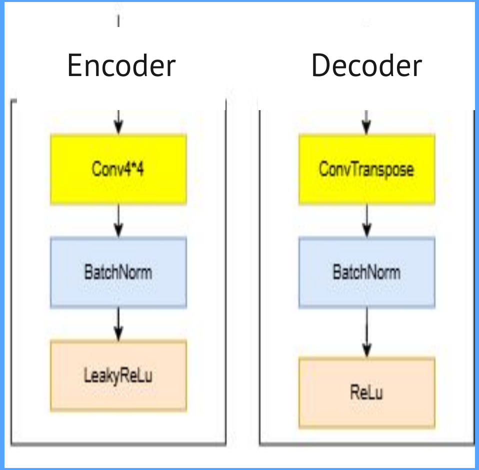

Fig 10. Structure inside the encoder and decoder.

Results

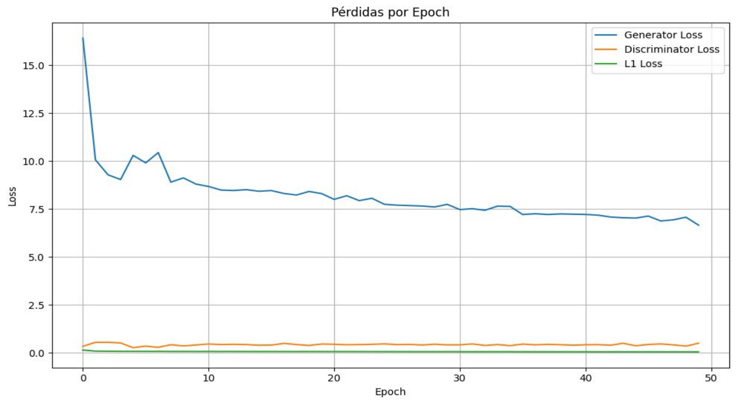

Fig 11. Generator and discriminator loss

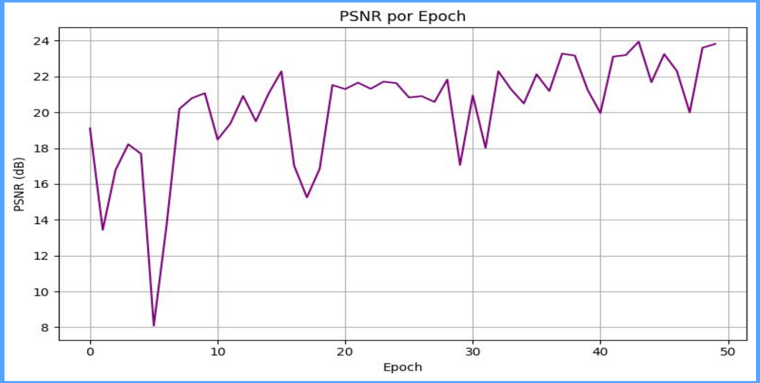

Fig 12. Generator PSNR

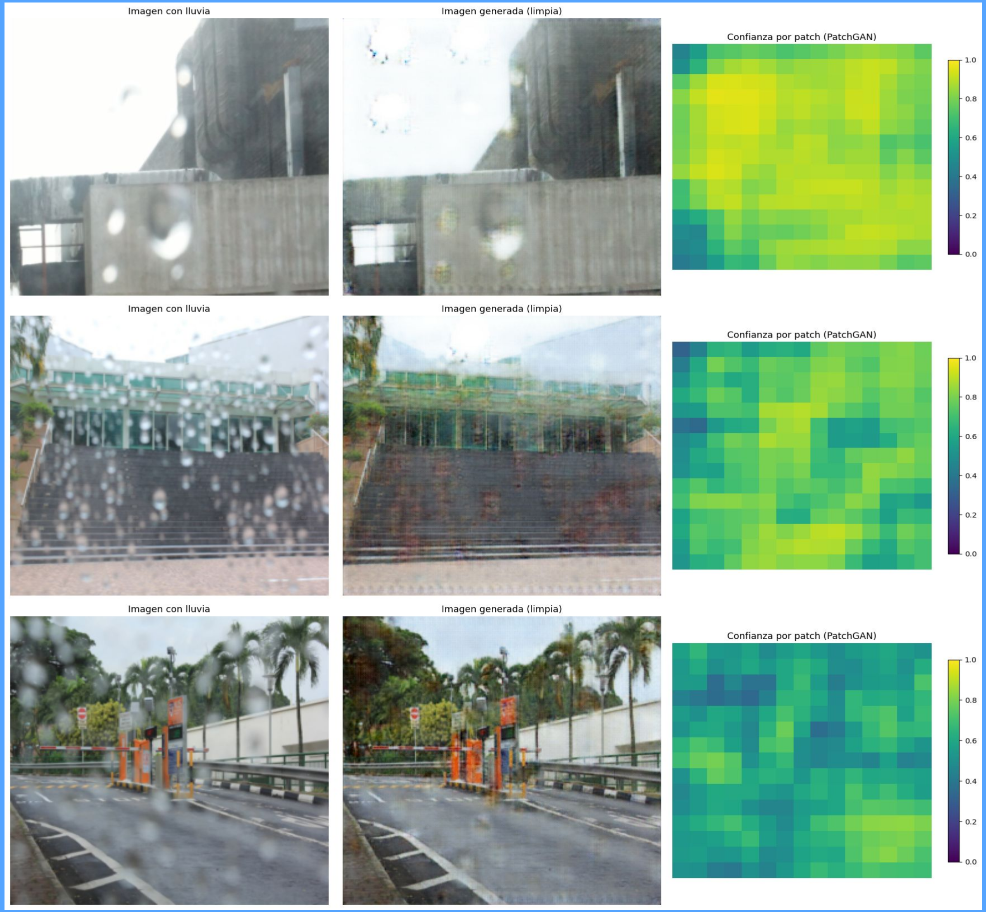

Fig 13. Result images

3. Discriminator penalties

Common problem:

Very common problem in GAN is the discriminator overpowering the generator

- **Balance the Training**: Train the Generator more often than the Discriminator.
- **Label Smoothing:** Apply soft labels; use 0.9 for real and 0.1 for fake instead of 1 and 0.
- **Use Noisy Labels:** Occasionally flip labels (e.g., 5–10% of the time, label fake as real).
- **Change Learning Rates:** Discriminator and generator should not have the same learning rate, and the generator should learn faster than the discriminator.

What penalties have we used:

Generator learning rate: 0.0005
Discriminator learning rate: 0.0002

Probability of real → 0.9
Probability of fake → 0.1

Why?

- Easier to implement
- We didn't know how much the penalties would affect, if positive we could potentially add more

Results

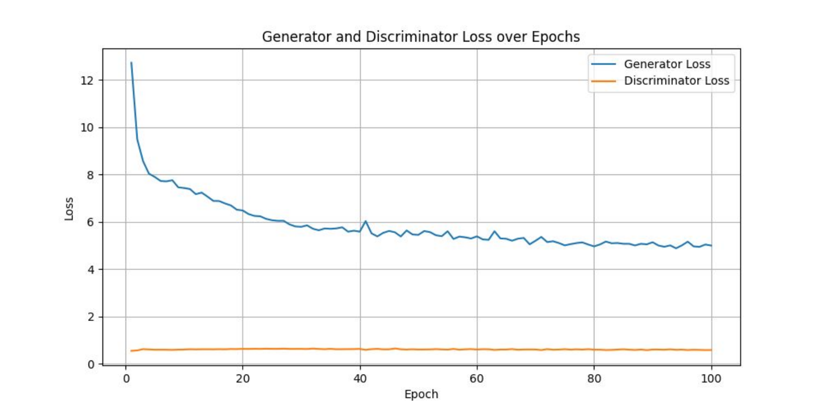

Fig 14. Generator and discriminator loss

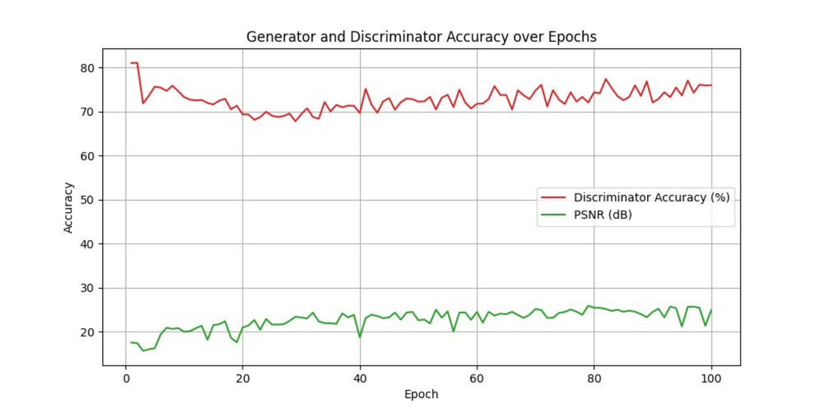

Fig 15. Generator PSNR and discriminator accuracy

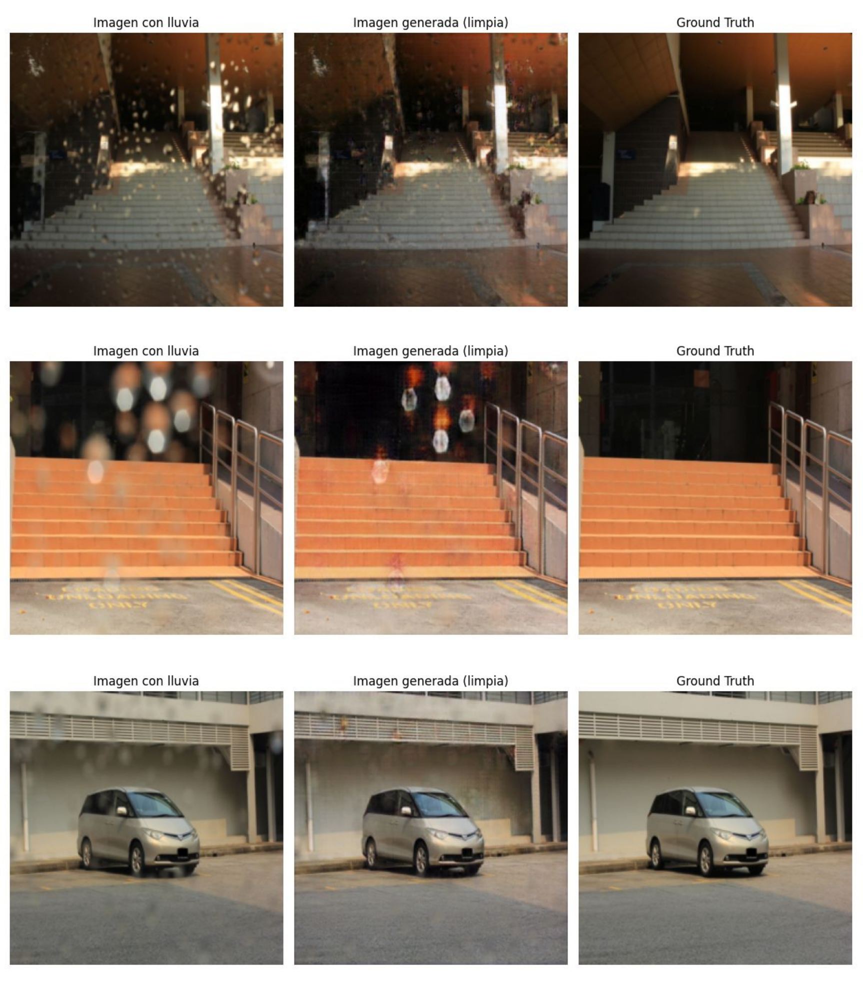

Fig 16. Result images

5. Challenges

Challenges

Challenges:

- Time: 1 hour approximately to train the model
- Still the water drop are a bit visible

Ideas / Next steps:

- For the white spots: add contrastive loss
- For the ones with more raindrop, data augmentation

References

[1] Staff, C. (2024, September 18). What is a conditional generative adversarial network? Coursera. https://www.coursera.org/articles/conditional-generative-adversarial-network

[2], Fig1: TaskUs. (2024, February 13). CGANs 101: What is a Conditional Generative Adversarial Network? | TaskUs. https://www.taskus.com/insights/cgans-101-what-is-a-conditional-generative-adversarial-network/

Fig2: Khan, Umair & Koivukoski, Sonja & Valkonen, Mira & Latonen, Leena & Ruusuvuori, Pekka. (2023). The effect of neural network architecture on virtual H&E staining: Systematic assessment of histological feasibility. Patterns. 4. 100725. 10.1016/j.patter.2023.100725.

Fig3: Qian, R., Tan, R. T., Yang, W., Su, J., & Liu, J. (2017, November 28). Attentive Generative Adversarial Network for Raindrop Removal from a Single Image. arXiv.org. https://arxiv.org/abs/1711.10098

[3] Isola, P., Zhu, J., Zhou, T., & Efros, A. A. (2016, 21 noviembre). *Image-to-Image Translation with Conditional Adversarial Networks*. arXiv.org. https://arxiv.org/abs/1611.07004v3

THANKS FOR YOUR ATTENTION