



Bringing old photos back to life



[Original github link](#)

...

[Our github link](#)



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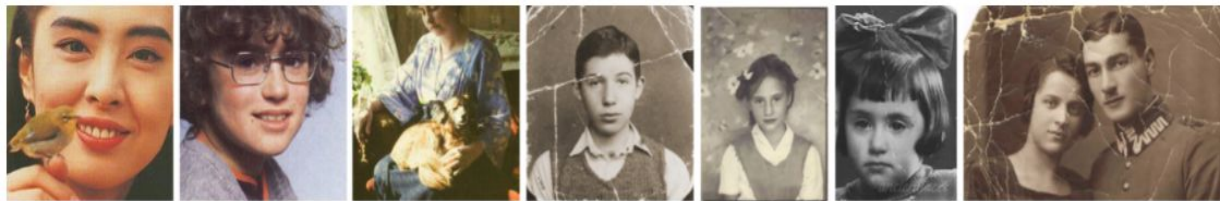
...

01

Introduction

Photo restoration

BEFORE



AFTER



Ziyu Wan

Bo Zhang

Dongdong Chen

Pan Zhang

Dong Chen

Jing Liao

Fang Wen

City University of Hong Kong

Microsoft Research Asia

Microsoft Cloud AI

USTC

Two Types of degradations



Unstructured

1. Blurriness
2. Noise
3. Low resolution
4. Sepia issue



Structured

1. Scratches
2. Holes
3. Spots

Previous work

Real image



Output



Domain gap



Synthetic image

Previous work



Structured defect

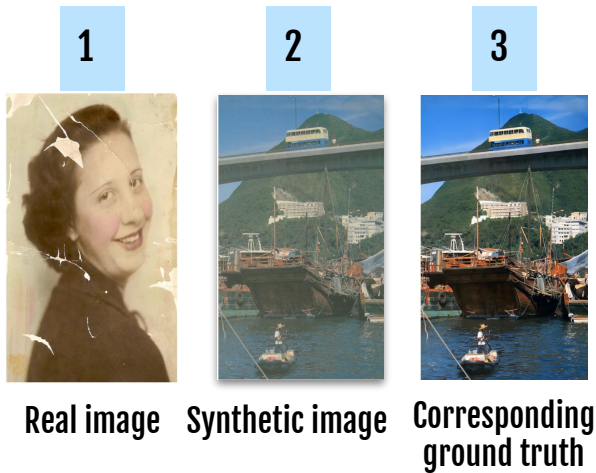
or



Unstructured defect

- Focused on either structured or unstructured errors
- Used synthetic data only for training
- Unsatisfied output

This paper



Structured defect

&



Unstructured defect

- This project proposes **a triplet domain** translation network to restore the mixed degradation in old photos.
- Deals with **both structured and unstructured** defects

02

Method

Two problems and respective solution

01

Generalization issue

There always exists a **domain gap** between **synthetic** and **real photos**.

Real \neq Synthetic



Restoration via latent space translation

02

Mixed degradation issue

The defects of old photos are a **compound** of multiple degradations. Different types of defects necessitate **different methods** to solve.

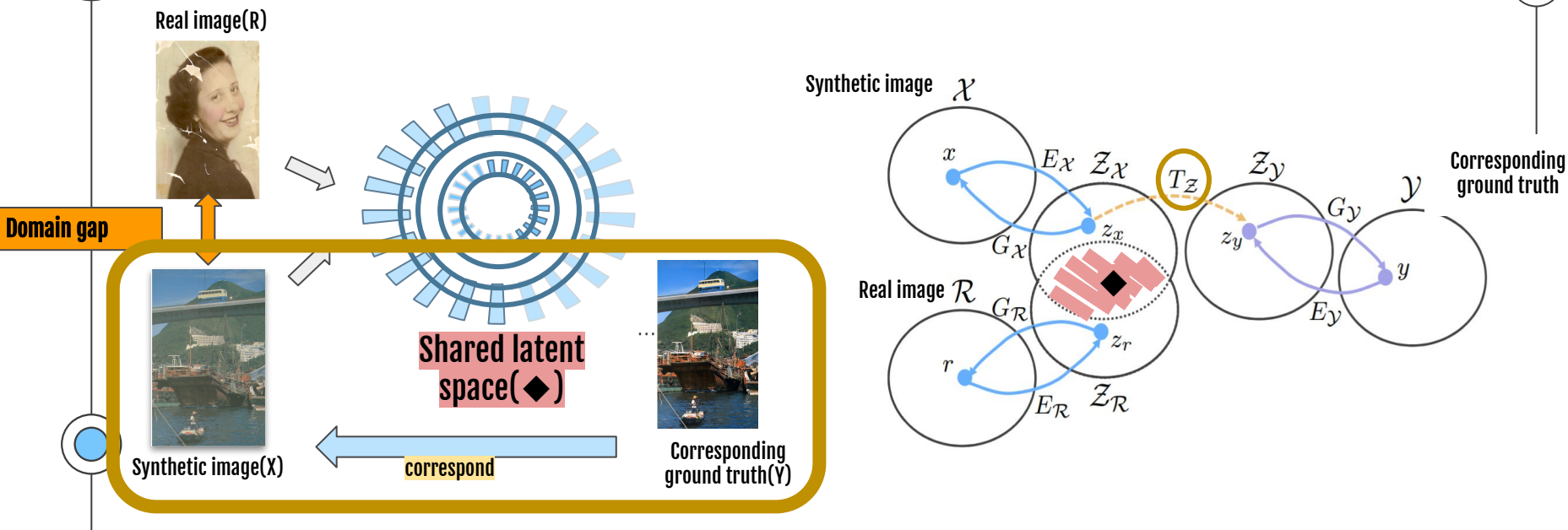
film noise, blurriness and color fading ...
scratches and blotches ...



Multiple degradation restoration

solutions

Restoration via latent space translation

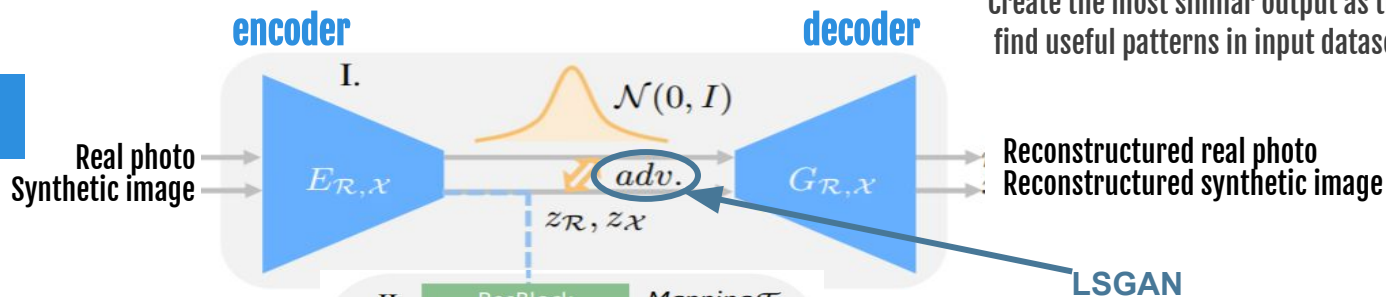


- Solves generalization issue by restoration via latent space(Z) translation among three domains: R, X, Y .
- To mitigate the domain gap, this project aligns latent spaces of synthetic images and real old photos into the shared domain, which encodes features for all the corrupted images, either synthetic or real ones by first VAE.
- Learn the translation from the latent space of corrupted images($Z_{\mathcal{X}}$) to the latent space of ground truth($Z_{\mathcal{Y}}$)

Architecture of network

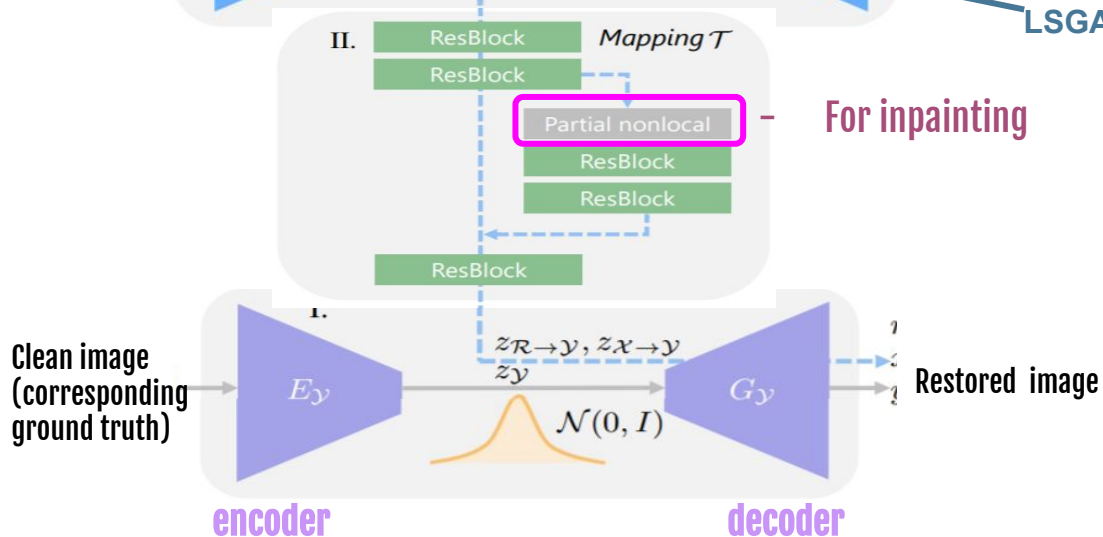
- Objective of Variational AutoEncoder(VAE):
Create the most similar output as the input and find useful patterns in input datasets.

VAE #1



Mapping

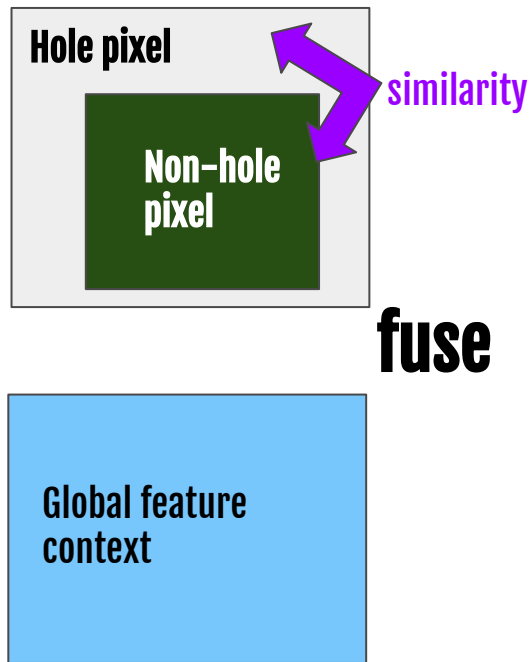
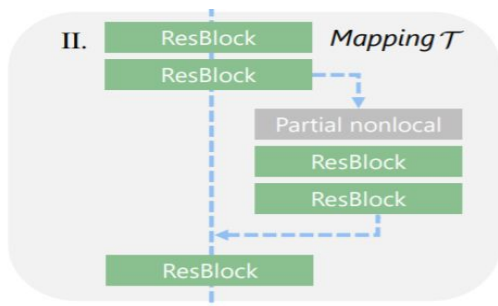
VAE #2



Multiple degradation restoration

For inpainting

Mapping



- Calculate similarity between non-hole pixel and hole pixel
- Fuse the non-hole pixel using global feature context
- Make a new feature map

Architecture in details

Pix2Pix model



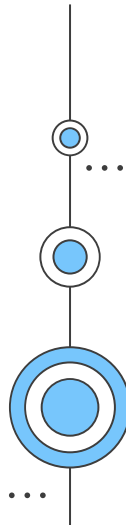

Module	Layer	Kernel size / stride	Output size
Encoder E	Conv	$7 \times 7/1$	$256 \times 256 \times 64$
	Conv	$4 \times 4/2$	$128 \times 128 \times 64$
	Conv	$4 \times 4/2$	$64 \times 64 \times 64$
	ResBlock $\times 4$	$3 \times 3/1$	$64 \times 64 \times 64$
Generator G	ResBlock $\times 4$	$3 \times 3/1$	$64 \times 64 \times 64$
	Deconv	$4 \times 4/2$	$128 \times 128 \times 64$
	Deconv	$4 \times 4/2$	$256 \times 256 \times 64$
	Conv	$7 \times 7/1$	$256 \times 256 \times 3$
Mapping \mathcal{T}	Conv	$3 \times 3/1$	$64 \times 64 \times 128$
	Conv	$3 \times 3/1$	$64 \times 64 \times 256$
	Conv	$3 \times 3/1$	$64 \times 64 \times 512$
	Partial Non-local	$1 \times 1/1$	$64 \times 64 \times 512$
	Resblock $\times 2$	$3 \times 3/1$	$64 \times 64 \times 512$
	ResBlock $\times 6$	$3 \times 3/1$	$64 \times 64 \times 512$
	Conv	$3 \times 3/1$	$64 \times 64 \times 256$
	Conv	$3 \times 3/1$	$64 \times 64 \times 128$
	Conv	$3 \times 3/1$	$64 \times 64 \times 64$
	Conv	$3 \times 3/1$	$64 \times 64 \times 64$



03

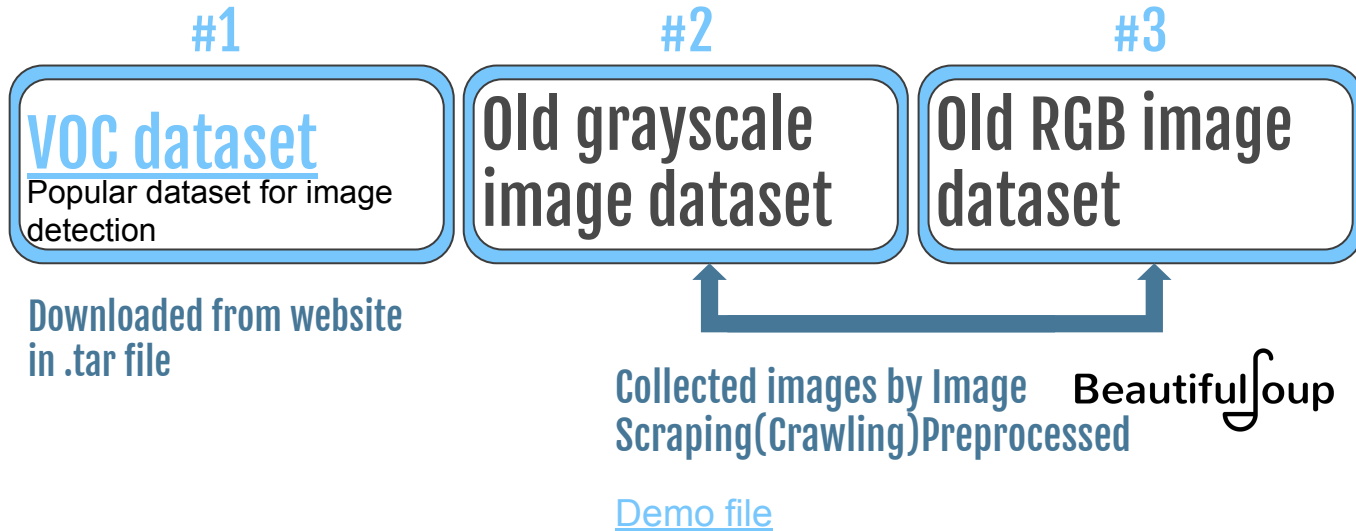
Dataset

Enter a subtitle here if you need it



3 Datasets needed for training

None of the datasets were given in the project.



04

Implementation in Code Demo

3 parts of training

Training dataset Trained model

01

Train_domain_A.py

We train VAE1 to encode real old images and synthetic "old" images into a shared latent space

02

Train_domain_B.py

We train VAE2 to encode the clean images (ground truth)

03

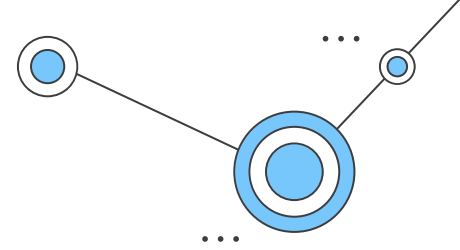
Train_mapping.py

We learn the mapping that restores the corrupted images to the clean images in the latent space.

Training via transfer learning demo

https://colab.research.google.com/drive/1HO_8oQ2himYgib0z4RV6vH00VZa0Vdz7?usp=sharing

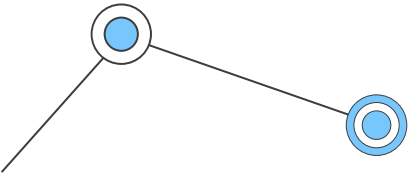
Testing the model



Testing demo

<https://colab.research.google.com/drive/1jS4faSuP3XHausSADuYA4wcC4-hmhjqU?usp=sharing>

[Tested image](#)






05

Evaluation

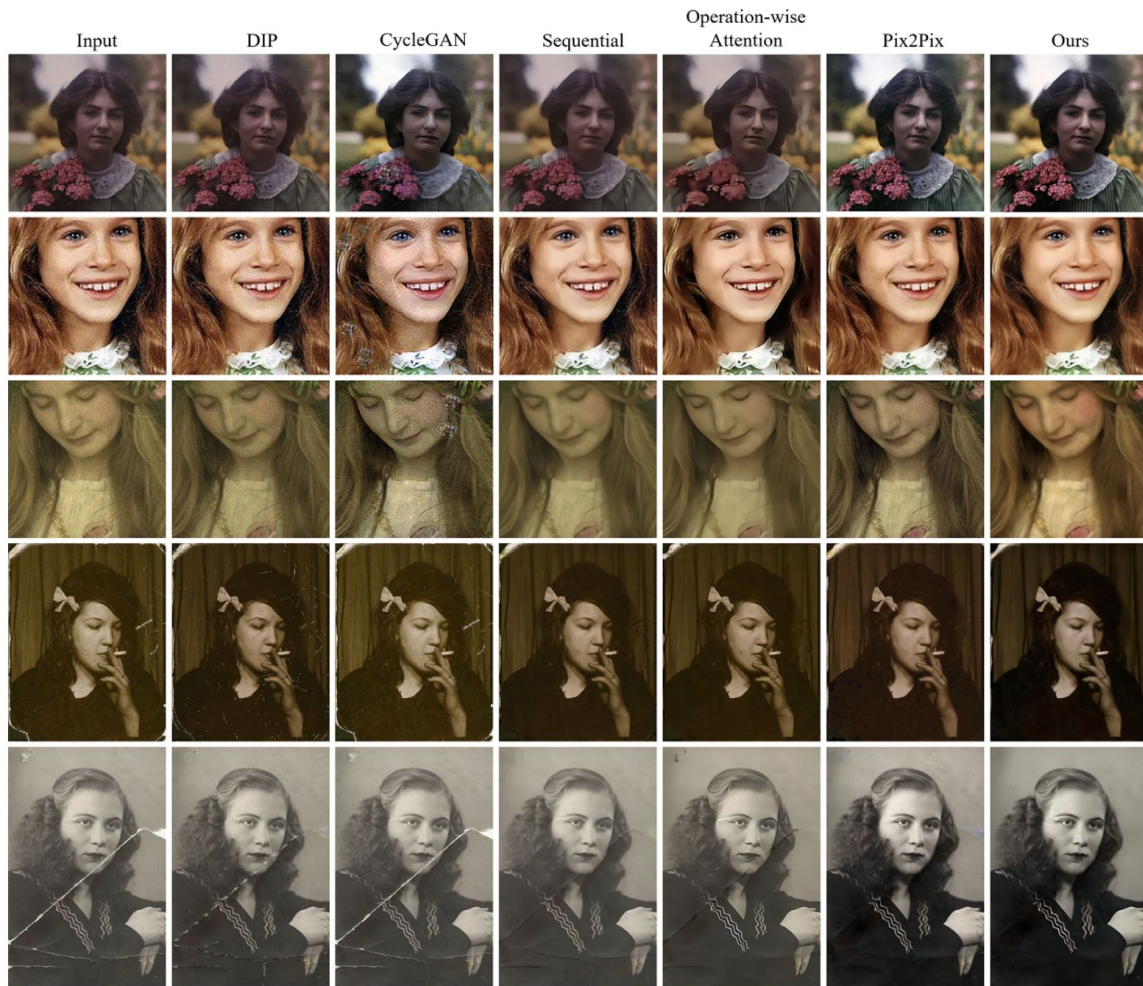
Enter a subtitle here if you need it



Quantitative analysis

	Metrics			
Method	PSNR	SSIM	LPIPS	FID
Input	12.92	0.49	0.59	306.80
Attention	24.12	0.70	0.33	208.11
DIP	22.59	0.57	0.54	194.55
Pix2Pix	22.18	0.62	0.23	135.14
Sequential	22.71	0.60	0.49	191.98
New model w/o PN	23.14	0.68	0.26	143.62
New model w PN	23.33	0.69	0.25	134.35

Qualitative analysis



User study

	User selection (percentage)				
Method	Top 1	Top 2	Top 3	Top 4	Top 5
DIP	2.75	6.99	12.92	32.63	69.70
Cycle GAN	3.39	8.26	15.68	24.79	52.12
Sequential	3.60	20.97	51.48	83.47	93.64
Attention	11.22	28.18	56.99	75.85	89.19
Pix2Pix	14.19	54.24	72.25	86.86	96.61
New model	64.83	81.35	90.68	96.40	98.72



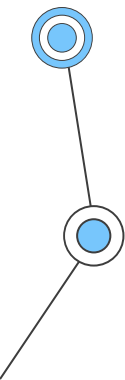
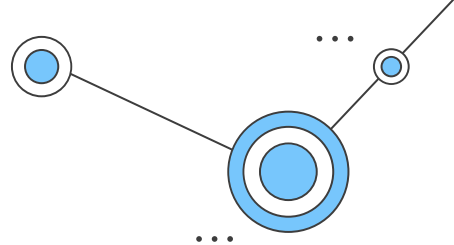
06

Conclusion and Project Challenges

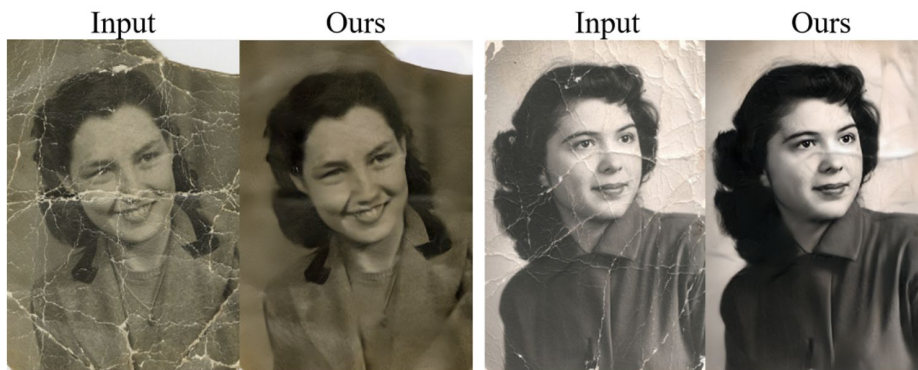


Conclusion

- This project developed a triplet domain translation network to restore both structured and unstructured defects in old photos.
- The domain gap is reduced between old photos and synthetic images.
- The translation to clean images is learned in latent space.
- This method suffers less from generalization compared to other methods.
- The writers propose a partial nonlocal block which restores the latent features by taking the global context into account. This way the scratches can be restored consistently.
- This method demonstrates good performance even in severely degraded old photos.



Project challenges



1. This method cannot handle complex shading.

The authors believe this is because the training dataset contained few photos with this defect.

a.png



b.png

b.png

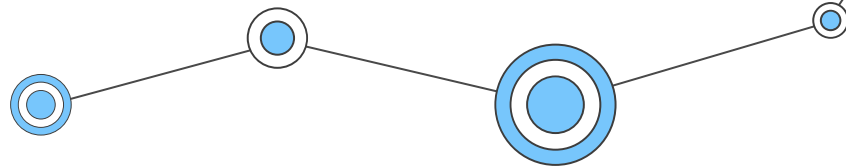


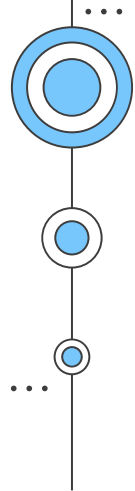
c.png



Project challenges

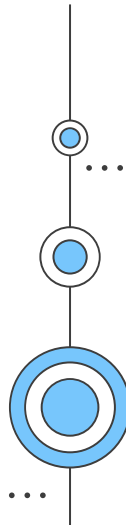
2. This model does not inpaint large holes in corners / borders





07

Challenges



Challenges



Colab crashing often

The colab crashed often, for not specific reasons. It was not due to the GPU, RAM, or run-time error. But we fixed it by decreasing the size of the image datasets, and keep on trying to make it work.



Due to errors, code modifications were needed

There were a lot of errors, but we solved it through searching the errors in google, referring to the 'issue' page in the github, and trying new different things like changing hyper parameters.



Heavy memory space

We were not able to run it locally in visual studio code, jupyter notebook or virtual machine, but could only run it through colab remotely because the size of the project was too large



Datasets were not given

The project required 3 datasets, but none of them was given. So it was not only hard to image crawl, but defer which image is apt to train for this project.



Image crawling

It was our first time doing image scraping, so we were not accustomed to the tools for image crawling. Also, finding old RGB images was hard because there weren't sufficient number of images per each website, so we visited about 30 websites to prepare the dataset for RGB.



Environment not matching

We initially wanted to run each file independently, without the given training command. However, it was not possible in the windows environment. So, we had to change the bash commands or commands for linux to work in colab or Windows environment.



Many independent files

As there were many independent .py files in the project, it was hard to figure out how each files relate, and in what order they were running. Therefore, we inserted codes to print out the name of the function when the function was called



math equations and symbols

Understanding the objective function or loss function was hard because there were many kinds of models combined in this one project. Therefore, without beginning with the codes, we took an effort to understand the math part first by studying [VAE](#) and [GAN](#) in Notion



Taking a long time to train

Whenever we got an error, and the training stopped due to that error, and we had to restart training from the very beginning. And the training took very long time, so we were afraid we might not be able to finish training the whole model in time. But, we solved this problem by reducing the size of image datasets and solving errors.



**Thank
you**

