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Dual GAN-based Translation of Satellite Imagery to Google Map Representation for Enhanced Geospatial Analysis

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ABSTRACT_ Image translation has become widely used in a variety of applications, including generating avatars, making fake photos, translating images from one kind to another, and many more, all employing various machine learning methods. One such machine learning technique for picture translation is GAN (Generative Adversarial Networks). Classic GANs translate the images of a domain U to domain V, whereas conditional GANs do the same but under certain conditions. These GANs can accurately determine the discriminating between items when training labeled data sets, however they cannot perform well while training unlabeled data sets.So, we need a GAN that can train unlabeled data sets well, translate images from domain U to domain V, and determine the realness or fakeness of the translated image using the original image as a reference. For this aim, we investigate dual GANs, which combine a primal GAN with another GAN. Dual GAN learns the inversion of the primal GAN's task, which is comparable to the standard GAN.

Keywords: Generative Adversarial Networks, Dual GANs, Classic GANS, Machine Learning, Generator, Discriminator, Image translation, Neural networks, Conditional GANs, Standardization

1.INTRODUCTION

In this paper, we will study how actually Dual GANs work for translation of images. The dataset that is being trained for this paper is “maps”. The data set consists of the satellite images and the corresponding Google map images. The size of each image is 600x600 pixels. The image translation involves translating satellite image to Google map images and Google map images to satellite images. The generator

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and the discriminator are the major parts of the architecture of the GAN model. The generator is an encoder-decoder which takes an input or source image (eg. satellite image) and converts it into target image (eg. Google map image) using a U-Net architecture [12]. Using a deep convolutional neural network i.e, the discriminator that discriminates the image generated with that of the source image and predicts the realness or fakeness of the translated image [12]. Basically, Dual GANs consists of a primal GAN which translates pictures from a domain U to domain V and inversion of the primal GAN is taken care of by the secondary GAN simultaneously. Dual GANs are used in this project because when training unlabeled data, they perform very well at generating some of the best images with high precision and accuracy compared to GANs and CGANs.

2.LITERATURE SURVEY

Ref. No.	S.No	Title of the Paper	Authors	Findings
[2]	1	SPI-GAN: Towards Single-Pixel Imaging through Generative Adversarial Network	Nazmul Karim and Nazanin Rahnavard	SPI-GAN is a generative adversarial network-based method for single-pixel imaging. It uses a ResNet-like architecture for the generator to learn useful representations, allowing for reconstruction of completely unseen objects. The experimental results demonstrate that SPI-GAN outperforms the current state-of-the-art method and has better generalization ability to completely unseen datasets. This method has the potential to enable low-cost and high-speed imaging, making it an exciting development in the field of image recovery.

[3]	2	LinkGAN: Linking GAN Latents to Pixels for Controllable Image Synthesis	Jiapeng Zhut, Ceyuan Yangt, Yujun Shent, Zifan Shi, Deli Zhao, Qifeng Chen	LinkGAN allows for local control of image synthesis by linking specific image regions to latent space axes during GAN training. The experimental results show that LinkGAN has several desirable properties, including the ability to link multiple regions to different latent axes independently and simultaneously, without sacrificing synthesis performance. This method improves spatial controllability in both 2D and 3D GAN models and enhances GAN-based image synthesis. This work is significant in the development of more spatially controllable and disentangled GAN latent spaces.
[4]	3	Attention-Guided Generative Adversarial Networks for Unsupervised Image-to-Image Translation	Hao Tang, Dan Xu, Nicu Sebe, Yan Yan	AGGAN is a GAN-based approach for semantic manipulation problems. AGGAN detects most discriminative semantic object and minimizes changes to unwanted parts, resulting in high-quality images. AGGAN uses attention-guided generators and a novel attention-guided discriminator to produce attention masks and content masks. The results show that AGGAN out performs existing models and has potential applications in various fields such as computer vision and medical imaging.

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[5]	4	Image-To-Image Translation with Conditional Adversial Networks	Phillip Isola, Jun-Yan Zhu ,Tinghui Zhou, Alexei A.Efros	The authors investigate that conditional adversarial networks are used in solving the image-to-image translation. These networks have input image to output image mapping and it also has a loss function to train this mapping. Convolutional Neural Nets (CNN) learn to minimize a loss function which is nothing but the objective that scores the quality of results.

3.PROPOSED WORK

DualGAN trains two trustworthy image translators from one domain to another at the same time, utilizing two sets of unlabeled photos as input, one for each image domain. As a result, DualGAN can handle a variety of image-to-image translation problems. Comparisons with GAN (with the original discriminator and an image-conditioned generator) and conditional GAN show DuanGAN's effectiveness. According to the comparison results, DualGAN outperforms supervised approaches built using labeled data in various applications. The main purpose of our project is to translate satellite photographs into Google Maps images and vice versa. Using DualGANs for this project improves dataset training and produces better results than GANs and Conditional GANs. DualGANs produce clearer translated images with more promising results.

3.1 IMPLEMENTATION

- Data collection: Collection of data set(maps).
- Data training: Training the dataset by applying DualGAN (Machine Learning and Neural Networks domain) algorithm and obtain the training output logs.
- Data testing: Testing the trained data.
- Analyze the training output logs.
- Given two sets of unlabeled and unpaired images sampled from domains U and V. The primal task of DualGAN is to learn a generator GA : U → V that maps an image u ∈ U to an image v ∈ V. While the dual task is to train an inverse generator GB : V → U. To realize this, we employ two GANs, the primal GAN and the dual GAN. The primal GAN learns the generator GA and a discriminator DA that discriminates

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between GA's fake outputs and real members of domain V. Similarly, the dual GAN learns the generator GB and a discriminator DB

This can be algorithmically defined as follows:

- Step-1: Import two sets of unlabeled, unpaired photos (x and y) drawn from the domains X and Y, respectively
- Step-2: Learn a generator G_A: X→Y that maps an image x∈X to an image y∈Y
- Step-3: Train an inverse generator G_B: Y→X that learns to map an image y∈Y to an image x∈X
- Step-4: Learn a discriminator D_A that compares real image from domain Y with that output of G_A's
- Step-5: Train an inverse discriminator D_B that compares real image from domain X with that of G_B's output

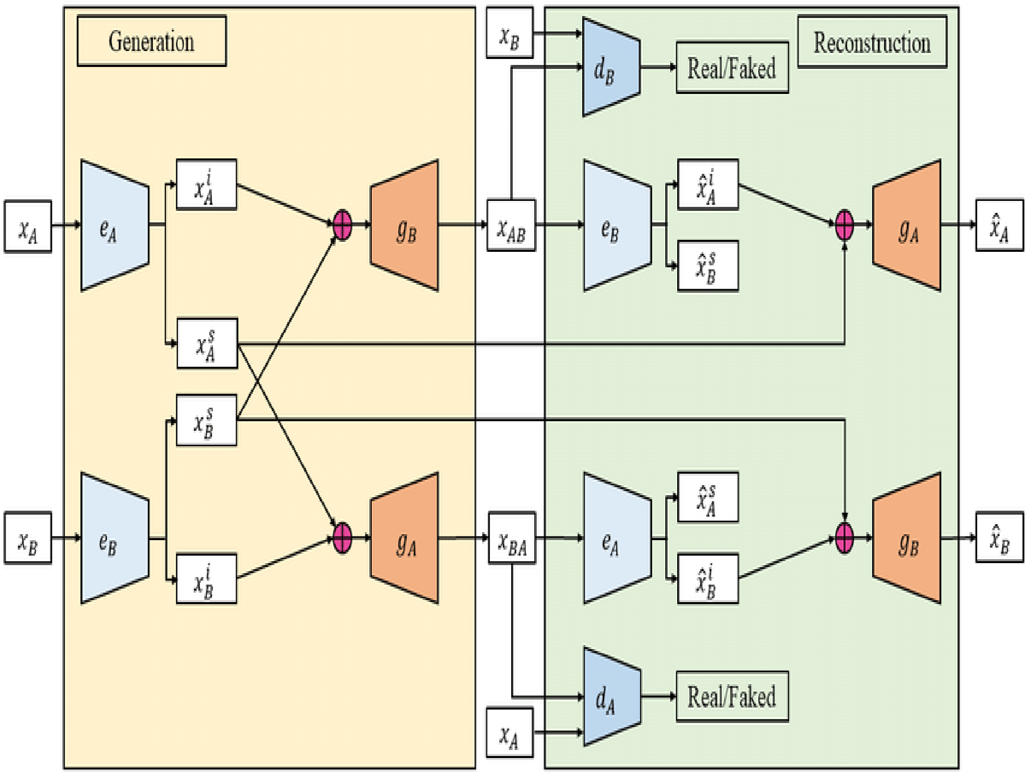


Figure-.1 Architecture of the Dual GAN System

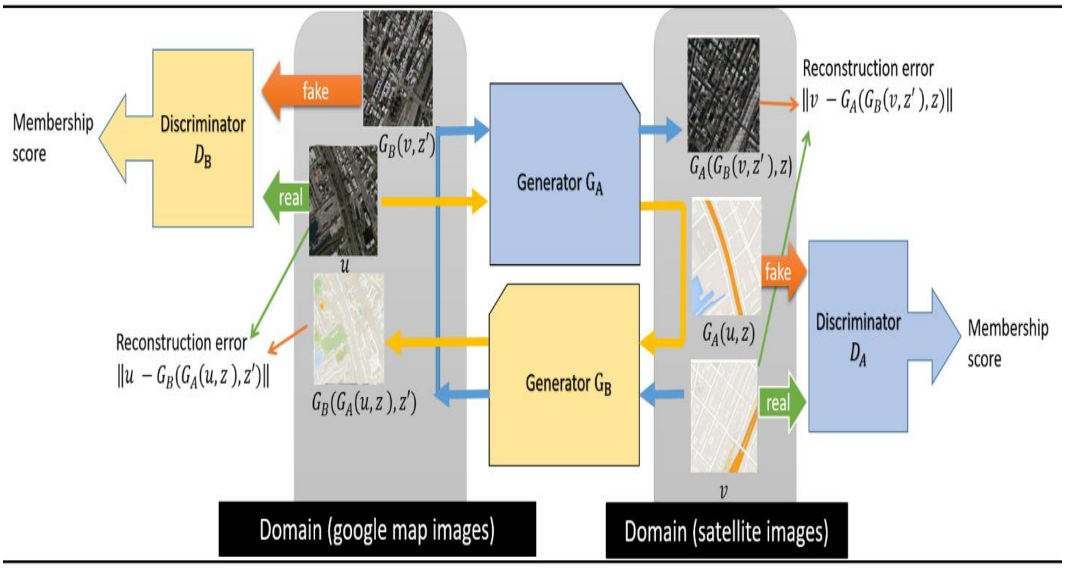
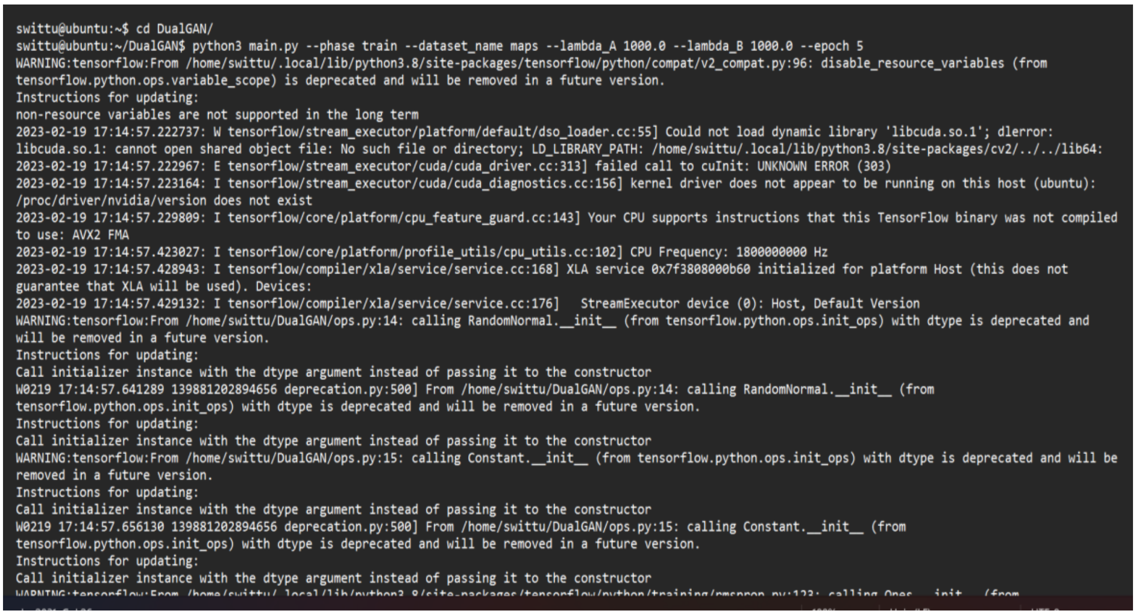


Figure-.2 Workflow diagram

4.RESULTS AND DISCUSSION

The following is the screenshot of how output looks when executed in terminal:



```
swittu@ubuntu:~$ cd DualGAN/
swittu@ubuntu:~/DualGAN$ python3 main.py --phase train --dataset_name maps --lambda_A 1000.0 --lambda_B 1000.0 --epoch 5
WARNING:tensorflow:From /home/swittu/.local/lib/python3.8/site-packages/tensorflow/python/compat/v2_compat.py:96: disable_resource_variables (from
tensorflow.python.ops.variable_scope) is deprecated and will be removed in a future version.
Instructions for updating:
non-resource variables are not supported in the long term
2023-02-19 17:14:57.222737: W tensorflow/stream_executor/platform/default/dso_loader.cc:55] Could not load dynamic library 'libcuda.so.1'; dlerror:
libcuda.so.1: cannot open shared object file: No such file or directory; LD_LIBRARY_PATH: /home/swittu/.local/lib/python3.8/site-packages/cv2/../../lib64:
2023-02-19 17:14:57.222967: E tensorflow/stream_executor/cuda/cuda_driver.cc:313] failed call to cuInit: UNKNOWN ERROR (303)
2023-02-19 17:14:57.223164: I tensorflow/stream_executor/cuda/cuda_diagnostics.cc:156] kernel driver does not appear to be running on this host (ubuntu):
/proc/driver/nvidia/version does not exist
2023-02-19 17:14:57.229809: I tensorflow/core/platform/cpu_feature_guard.cc:143] Your CPU supports instructions that this TensorFlow binary was not compiled
to use: AVX2 FMA
2023-02-19 17:14:57.423027: I tensorflow/core/platform/profile_utils/cpu_utils.cc:102] CPU Frequency: 1800000000 Hz
2023-02-19 17:14:57.428943: I tensorflow/compiler/xla/service/service.cc:168] XLA service 0x7f3808000b60 initialized for platform Host (this does not
guarantee that XLA will be used). Devices:
2023-02-19 17:14:57.429132: I tensorflow/compiler/xla/service/service.cc:176]   StreamExecutor device (0): Host, Default Version
WARNING:tensorflow:From /home/swittu/DualGAN/ops.py:14: calling RandomNormal.__init__ (from tensorflow.python.ops.init_ops) with dtype is deprecated and
will be removed in a future version.
Instructions for updating:
Call initializer instance with the dtype argument instead of passing it to the constructor
W0219 17:14:57.641289 139881202894656 deprecation.py:500] From /home/swittu/DualGAN/ops.py:14: calling RandomNormal.__init__ (from
tensorflow.python.ops.init_ops) with dtype is deprecated and will be removed in a future version.
Instructions for updating:
Call initializer instance with the dtype argument instead of passing it to the constructor
WARNING:tensorflow:From /home/swittu/DualGAN/ops.py:15: calling Constant.__init__ (from tensorflow.python.ops.init_ops) with dtype is deprecated and will be
removed in a future version.
Instructions for updating:
Call initializer instance with the dtype argument instead of passing it to the constructor
W0219 17:14:57.656130 139881202894656 deprecation.py:500] From /home/swittu/DualGAN/ops.py:15: calling Constant.__init__ (from
tensorflow.python.ops.init_ops) with dtype is deprecated and will be removed in a future version.
Instructions for updating:
Call initializer instance with the dtype argument instead of passing it to the constructor
```

Figure-2: Screenshot-1 of output in the console

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```
Instructions for updating:
Call initializer instance with the dtype argument instead of passing it to the constructor
W0219 17:15:05.337066 139881202894656 deprecation.py:500] From /home/swittu/.local/lib/python3.8/site-packages/tensorflow/python/training/rmsprop.py:123:
calling Ones.__init__ (from tensorflow.python.ops.init_ops) with dtype is deprecated and will be removed in a future version.
Instructions for updating:
Call initializer instance with the dtype argument instead of passing it to the constructor
 [*] Reading checkpoint...
INFO:tensorflow:Restoring parameters from ./checkpoint/maps-img_sz_256-fltr_dim_64-L1-lambda_AB_1000.0_1000.0/DualNet.model-102
I0219 17:15:29.701091 139881202894656 saver.py:1293] Restoring parameters from ./checkpoint/maps-img_sz_256-fltr_dim_64-L1-lambda_AB_1000.0_
1000.0/DualNet.model-102
 [*] Load SUCCESS
[*] training data loaded successfully
#data_A: 1794  #data_B:1794
[*] run optimizor...
time: 113.8850, Ad: -150.28, Ag: 147.02, Bd: -41.40, Bg: 177.09,  U_diff: 0.10893, V_diff: 0.04303
Ad_fake: -109.47, Ad_real: -40.81, Bd_fake: -69.51, Bd_real: 28.11
Epoch: [ 0] [   9/1794]
time: 177.5190, Ad: -3.91, Ag: 136.31, Bd: -18.29, Bg: 187.63,  U_diff: 0.10610, V_diff: 0.03808
Ad_fake: -85.90, Ad_real: 81.99, Bd_fake: -80.38, Bd_real: 62.09
Epoch: [ 0] [  19/1794]
time: 245.8369, Ad: -200.98, Ag: 165.96, Bd: -13.99, Bg: 158.82,  U_diff: 0.08222, V_diff: 0.05141
Ad_fake: -107.83, Ad_real: -93.15, Bd_fake: -75.09, Bd_real: 61.10
Epoch: [ 0] [  29/1794]
time: 296.1782, Ad: -0.95, Ag: 162.45, Bd: 54.21, Bg: 115.97,  U_diff: 0.06788, V_diff: 0.05445
Ad_fake: -103.05, Ad_real: 102.10, Bd_fake: -12.37, Bd_real: 66.59
Epoch: [ 0] [  39/1794]
time: 340.4330, Ad: -15.32, Ag: 172.89, Bd: -21.75, Bg: 188.58,  U_diff: 0.10176, V_diff: 0.05943
Ad_fake: -112.94, Ad_real: 97.62, Bd_fake: -80.05, Bd_real: 58.30
Epoch: [ 0] [  49/1794]
time: 378.9018, Ad: -13.64, Ag: 137.68, Bd: -28.73, Bg: 175.00,  U_diff: 0.10505, V_diff: 0.03817
Ad_fake: -100.95, Ad_real: 87.31, Bd_fake: -70.42, Bd_real: 41.69
Epoch: [ 0] [  59/1794]
time: 437.3969, Ad: -75.66, Ag: 139.31, Bd: -30.99, Bg: 164.54,  U_diff: 0.10387, V_diff: 0.04012
Ad_fake: -99.71, Ad_real: 24.06, Bd_fake: -57.70, Bd_real: 26.70
```

Figure-3: Screenshot-2 of output in the console

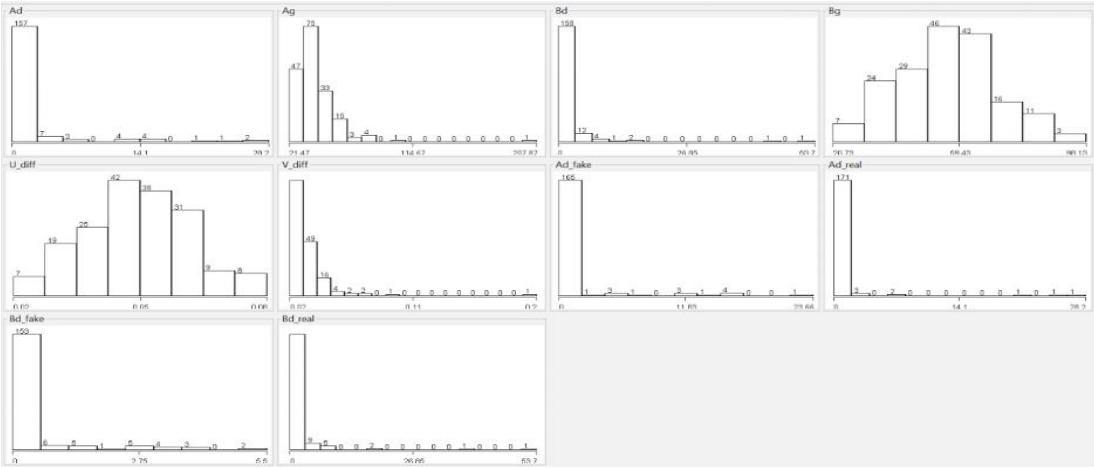

Figure-4: Statistics of the sample logs generated by the classic GAN

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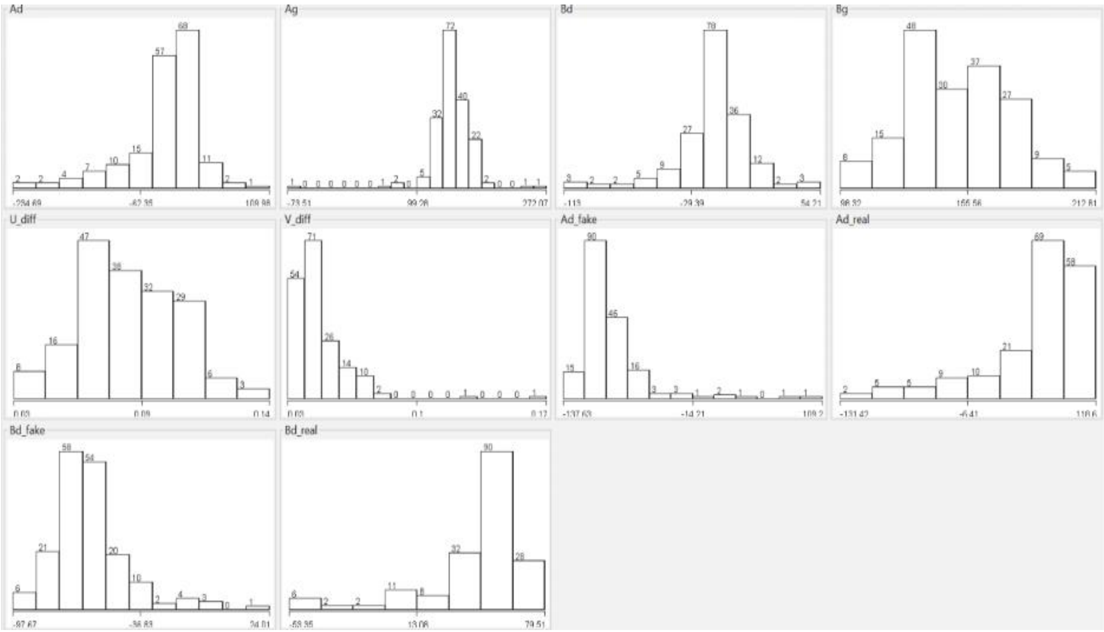

Figure-5 Statistics of the sample logs generated by the Dual GANs

5.CONCLUSION

Image translation is useful for creating new images from existing images by selecting the features of the original images. Based on the experiments and research, we can conclude that Dual GANs are reliable for predicting the likelihood of images formed during image translation of unlabeled image datasets. Classical GANs and conditional GANs, on the other hand, cannot surpass Dual GANs in terms of cross-domain translation and predicting the differences between the existing and produced images.When trained with unlabeled data, Dual GANs can do exceptionally well in picture translation and analysis, creating images from one dataset to another and vice versa. They can also differentiate images created from labeled datasets to some extent.

FUTURE SCOPE

The Dual GANs can be improvised so that they can perform well when used with labeled datasets. In future, they can be extended to carry out 3D image to image translations and analysis.

REFERENCES

1. Zili Yi, Hao Zhang, Ping Tan, Minglun Gong “DualGAN: Unsupervised Dual Learning for Image-to-Image Translation” arXiv: 1704.02510[cs.CV]
2. Nazmul Karim and Nazanin Rahnavard “SPI-GAN: Towards Single-Pixel Imaging through

Generative Adversarial Network" arXiv: 2107.01330[cs.CV]

3. Jiapeng Zhut, Ceyuan Yangt, Yujun Shent, Zifan Shi, Deli Zhao, Qifeng Chen "LinkGAN: Linking GAN Latents to Pixels for Controllable Image Synthesis" arXiv:2301.04604[cs.CV]
4. Hao Tang, Dan Xu, Nicu Sebe, Yan Yan "Attention-Guided Generative Adversarial Networks for Unsupervised Image-to-Image Translation" arXiv:1903.12296[cs.CV]
5. Phillip Isola, Jun-Yan Zhu ,Tinghui Zhou, Alexei A.Efros "Image-to-Image Translation with Conditional Adversarial Networks" arXiv:1611.07004[cs.CV]
6. Yaniv Taigman, Adam Polyak & Lior Wolf "Unsupervised Cross-Domain Image Generation" arXiv:1611.02200[cs.CV]
7. Xiang Chen , Jinshan Pan , Kui Jiang , Yufeng Li , Yufeng Huang , Chihuahua Kong , Long gang Dai , Zhentao Fan "Unpaired Deep Image Deraining Using Dual Contrastive Learning" arXiv:2109.02973[cs.CV]
8. Konstantinos Bousmalis , Nathan Silberman , David Dohan , Dumitru Erhan , Dilip Krishnan "Unsupervised Pixel-Level Domain Adaption with Generative Adversarial Networks" arXiv:1612.05424 [cs.CV]
9. Hadi Mansourifar , Steven J.Simske "Gan Based Object Removal in High Resolution Images" arXiv:2301.11726[cs.CV]
10. Edgar Schonfeld, Julio Borges, Vadim Sushko, Bernt Schiele, Anna Khoreva "Discovering Class-Specific GAN Controls for Semantic Image Synthesis" arXiv:2212.01455[cs.CV]

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