International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9s
DOI: https://doi.org/10.17762/ijritcc.v11i9s.7394
***Article Received**: 28 April 2023 **Revised:** 20 June 2023 **Accepted:** 16 July 2023*

Implementation of Super Resolution Techniques in Geospatial Satellite Imagery

Trupti Baraskar, Vignesh Charan Raman, Poojan Panchal
Dr Vishwanath Karad MIT World Peace University
School of Computer Engineering and Technology
Pune, Maharashtra, India
trupti.baraskar@mitwpu.edu.in, vigneshcharan26@gmail.com, pdavpoojan@gmail.com

Abstract— The potential for more precise land cover classifications and pattern analysis is provided by technological advancements and the growing accessibility of high-resolution satellite images, which might significantly improve the detection and quantification of land cover change for conservation. A group of methods known as "super-resolution imaging" use generative modelling to increase the resolution of an imaging system. Super-Resolution Imaging, which falls under the category of sophisticated computer vision and image processing, has a variety of practical uses, including astronomical imaging, surveillance and security, medical imaging, and satellite imaging. As computer vision is where deep learning algorithms for super-resolution first appeared, they were mostly created on RGB images in 8-bit colour depth, where the sensor and camera are separated by a few meters. But no evaluation of these methods has been done.

Keywords- Generative Adversarial Network; Machine learning; Image Processing; Noise Removal; Computer Vision.

I. INTRODUCTION

Multispectral and hyperspectral imagery has been used extensively for geospatial analysis over the past few decades. However, most computer vision algorithms and pertained models have not been trained or tested on the two aforementioned imagery until now since they have higher dimensionality ranging from four to dozens of bands. Geospatial analysis is of utmost importance for military-specific applications, including but not limited to cartography, war intelligence, battlefield management, terrain analysis, remote sensing, military installation management, and monitoring of conceivable terrorist activity. These applications sought super-resolution for upscaling the image resolution, thereby enhancing image sharpness, color correction, and zooming capabilities with a meager effect on image quality. On top of this, environmental and atmospheric factors like dusk, fog, haze, smog, rainfall, snow, clouds, and their shadows do not help the situation - making the captured imagery of terrestrial terrain less intelligible. Hence, super-resolution of satellite imagery is of paramount significance to get the best out of the available image at hand.

Generative modeling is well-researched for super-resolution, primarily on images with object distances less than a few meters. This project aims to model the RealESR algorithm based on Generative Adversarial Network for satellite imagery, wherein the algorithm will work on 12 bit and 16-bit images (unlike traditional 8-bit images) in a scalable and computationally inexpensive way. Furthermore, a flask-based GUI will be used for user-friendly interaction with the algorithm irrespective of the technical prowess of the end-user, which would also incorporate a development server and debugger, integrated support for unit testing and RESTful request dispatching.

The most recent super-resolution articles found evidence of mode dropping, which means that the model consistently produces approximately the same visual output throughout sampling (when conditioned on the same input). Most of the Super-Resolution Imaging research has been focused on human faces. It is debatable if these same architectures can be used for other domains like medical or astronomical imagery. The current approaches are computationally expensive, which calls for architecting a robust lightweight model.

II. LITRATURE REVIEW

This paper [1] shows show the process of enhancing an image's resolution from low resolution to high-resolution is known as image super resolution. To create low-resolution photographs from high-resolution ones, apply the formula below: Iy is the high-resolution image, Ix is the low resolution image, and D stands for the degradation function.

$$Ix = D(Iy)$$

Only the high resolution image and the equivalent low resolution image are supplied and the degradation parameters D and are unknown. The neural network's job is to identify the inverse function of deterioration using just the high resolution and low resolution image data. The following below figure 1

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9s
DOI: https://doi.org/10.17762/ijritcc.v11i9s.7394
***Article Received**: 28 April 2023 **Revised:** 20 June 2023 **Accepted:** 16 July 2023*

represents a few of the different methods utilized to complete this task.

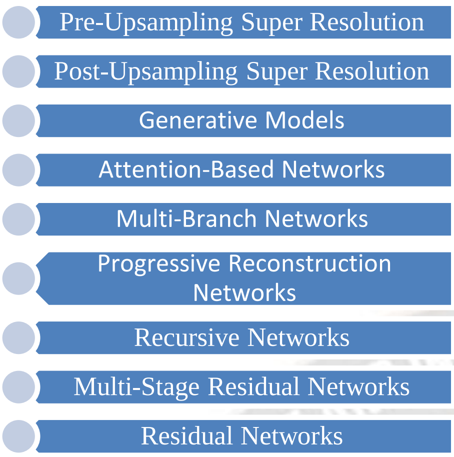


Figure 1. Different method for converting high resolution to low resolution image

In this study, shows [2] a brand-new picture super-resolution technique to enhance low-resolution image categorization performance. In order to identify the locations of the pixels in the ground truth HR image that contain more high frequency information, the approach introduces a weight map. This research paper [3] explores the state-of-the-art as it emerged from the NTIRE 2017 competition and introduces a fresh huge dataset for example-based single picture super-resolution. With six tournaments, hundreds of participants, and tens of solutions offered, the challenge is the first of its type. To automatically learn and fix the deformed scene features from a single remote sensing image, a generative adversarial network (GAN) architecture is proposed in this study [4]. The CNNs are evaluated on three well-known remote sensing datasets, along with a warped Yaogan-26 satellite image, in order to investigate the usability and efficacy of a GAN for jitter detection. The CNNs were trained on a portion of the PatternNet dataset. This paper [5] introduces a novel Chebyshev fractional-order differentiator-based image enhancing technique. They have created the high pass filter that corresponds to the Chebyshev fractional-order differentiator using Chebyshev polynomials. This study proposed [6] an upgraded GAN model that would use implicit direction from external geographic data to produce map images of higher quality. Additionally, a high-level semantic control is put in place to reduce the noisy patterns that translate in areas with little geographic data. One generator and two discriminators make up the suggested architecture, which aims to synthesize realistic cars while also learning the underlying information. According to trial results, this paper [7] proposed framework may produce vehicles and the scenery that surrounds them with variations and varied levels of detail. The GAN with reconstruction and style transfer losses and no encoder has been shown to be a practical model for producing maps in this paper [8]. The generator is trained as a normalizing flow (RealNVP) model and has a conditional Generative Adversarial Network (GAN) that compresses the images to a learned embedding. By utilizing cutting-edge deep neural network architectures, this paper [9] suggested super-resolution framework operating on overhead full-motion video and still imagery has addressed the issue of details being lost in the overhead remote sensing image due to sensor resolution and distance to a target. By super-resolving the obtained images, it is intended to retrieve such information, allowing automated visual exploitation techniques to be applied more successfully. In order to increase the resolution of DEMs, a GAN-based model (D-SRGAN) was created and evaluated in this research. It performs better than neural network algorithms and conventional statistical interpolation methods. This study paper [10] demonstrates how artificial neural networks' strength can be employed to boost DEM resolution. In order to create high-resolution semantic maps of buildings from middle-resolution satellite photos, it is crucial to investigate a deep-learning approach. The studied [11] network, which is known as FSRSS-Net and is based on super-resolution semantic segmentation features, is designed as a neural network that integrates low-level super-resolution image features and high-level super-resolution semantic features. It is trained using Sentinel-2A images (i.e., 10 m) and higher-resolution semantic maps (i.e., 2.5 m) images. This paper [12] has created Real-ESRGAN, a realistic restoration application that is trained on just synthetic data and uses the potent ESRGAN algorithm. Using high-order deterioration modelling, complex real-world degradations can be more accurately replicated. We also take common ringing and overshoot issues into consideration throughout the synthesizing process. The GAN model for blind SR tasks presented in this paper has a multi-scale attention U-Net discriminator that can be seamlessly combined with other generators. In order to address blind SR concerns, this research [13] is the first to employ an attention U-Net structure as a GAN discriminator. Additionally, the research clarifies the multi-scale attention U-Net's workings, giving the model a performance boost. In order to create an Enhanced SRGAN (ESRGAN), this paper [14] thoroughly analyze the three key SRGAN components of network architecture, adversarial loss, and perceptual loss in this study. We provide the Residual-in-Residual Dense Block (RRDB) without batch normalization as the fundamental unit of network design [15] [16].

For the purpose of expanding the work of super-resolution to be employed on geographical satellite imagery, the proposed work has adopted the approach of generative models. To generate images that are attractive to the eye, generative models, also known as GANs, work to enhance perceptual quality. SRGAN, for instance, uses a GAN-based architecture to produce

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9s
DOI: https://doi.org/10.17762/ijritcc.v11i9s.7394
***Article Received**: 28 April 2023 **Revised:** 20 June 2023 **Accepted:** 16 July 2023*

visually appealing images. It utilizes the SRResnet network architecture as a backend and takes advantage of a multi-task loss to enhance the results. Three terms make up the loss: MSE loss capturing pixel similarity, Perceptual similarity loss used to capture high-level information by using a deep net- work. Adversarial loss from the discriminator.

The proposed work uses the Real ESR GAN method, which builds on the strengths of a standard SRGAN to display the algorithm's findings on a user-friendly GUI built with Flask on the backend.

III. RESEARCH METHODOLOGY USED AND IMPLEMENTATION

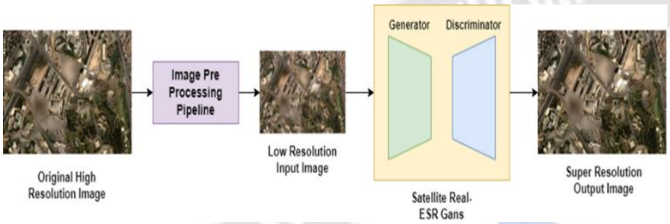


Figure 2. Original High Resolution to Super Resolution Conversion Process

The ground truth image from the dataset is shown by the original high resolution image in the figure 2. These images originate from the Google Maps dataset. Because the photos provide high resolution, we would need convert them to low resolution images in order to train the satellite's Real ESR GANs. In order to create images with a low resolution that are ideal for the model to train on, the dataset images are then put through the image pre-processing pipeline. While the discriminator differentiates between the images using ground truth photos, the generating model figure 3 for Satellite Real ESRGANs is trained using low resolution images. The model can generate extremely high resolution photos once it has been trained.

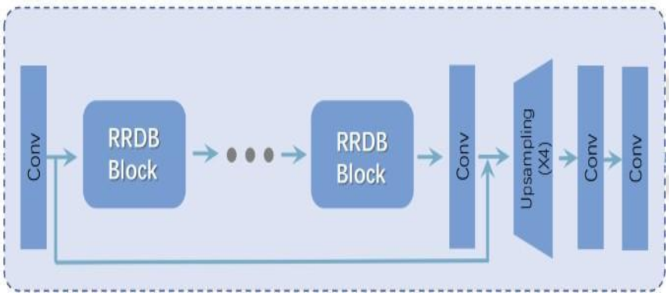


Figure 3. Real ESRGANs Architecture

A. Image Preprocessing Pipeline

By using multiple de-generation procedures, picture pre-processing pipelines assist in converting original high quality photos to low resolution images that are needed for training. The photos are initially blurred using two different techniques: The Gaussian filter and the 2D sinc filter. The second phase involves resizing every original image using several methods, such as bicubic, bilinear, and area-wise scaling. The photographs have various kinds of noise applied to them. Image compression is the last step in the pre-processing pipeline, and following this phase, images are prepared to be immediately entered into the model for training. Below figure 4 show the high resolution to low resolution image.

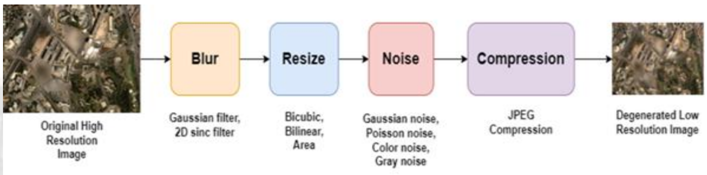


Figure 4. High Resolution to low resolution conversion process using image processing

B. Model Architecture Tree for Real ESR GANs

The diagram figure 5 provides a broad overview of how architecture of the model is created from different referenced papers. ESR GANs are the generation 1 GANs and the generator of this GANs was inherited from SR GANs whereas its discriminator was based on Relativistic GANs. The 2nd generation of ESR GANs known as Real ESR GANs has referred the generator from ESR GANs and discriminator is based on VGG style architecture which is modified to U-Net which spectral normalization (SN). This work proposed fine-tuned the Real-ESRGAN model with hyper parameters such as 100000 iterations, learning rate of 2x10^(-4), 500 epochs and early stopping.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9s
DOI: https://doi.org/10.17762/ijritcc.v11i9s.7394
***Article Received**: 28 April 2023 **Revised:** 20 June 2023 **Accepted:** 16 July 2023*

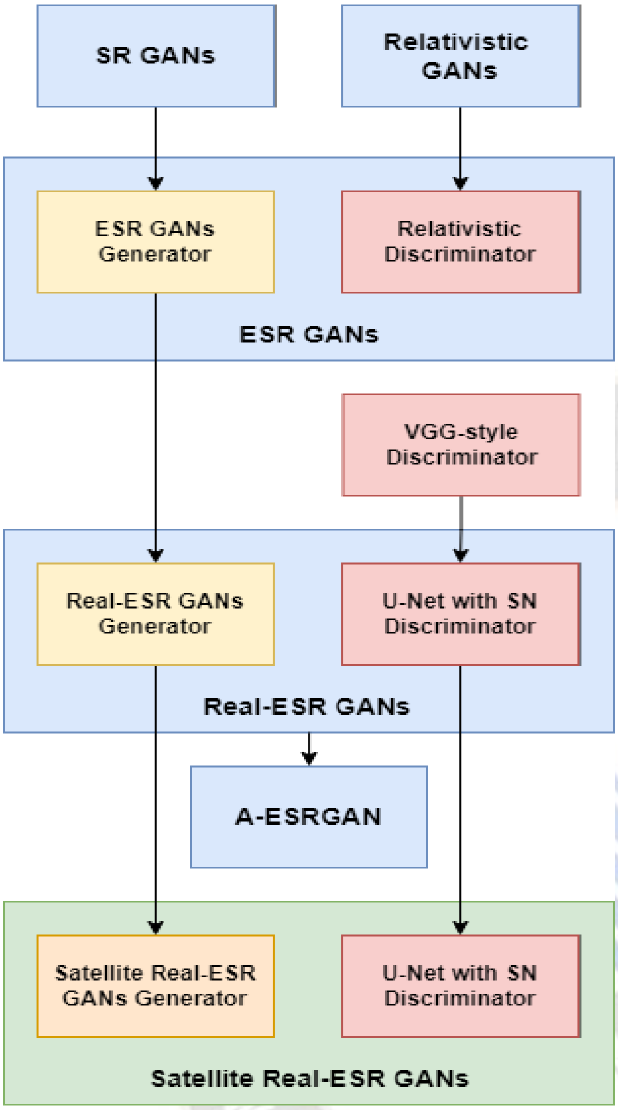


Figure 5. Model Architecture Tree for Real ESR GANs

The RealESR-GAN used in the proposed work makes use of a generator from a previous generation of super-resolution GANS, that is, ESRGAN. The algorithm also carries out super-resolution with a scale factor of x2 and x1 on the existing x4 ESRGAN architecture by using the pixel unsnuffing operation to reduce spatial size and increment channel size. As a result, the GPU memory as well as the performance of computational resources is utilized efficiently.

The implemented algorithm employs a U-Net architecture based discriminator added with skip connections which can provide the generator with an extensive per-pixel feedback. Furthermore, the discriminator has been equipped with spectral normalization technique to balance the training dynamics during GAN training.

IV. RESULT AND ANALYSIS

In order to evaluate the super resolution performed by the algorithm described in the earlier sections, we adopt peak signal-to-noise ratio (PSNR) as a metric. The PSNR block computes the peak signal-to-noise ratio, in decibels, between two images. This ratio is used as a quality measurement between the original and a compressed image.

$$PSNR = 10.\log_{10}\left(\frac{MAX_I^2}{MSE}\right)$$

$$PSNR = 20.\log_{10}\left(\frac{MAX_I}{\sqrt{MSE}}\right)$$

$$PSNR = 20.\log_{10}(MSE_I) - 20.\log_{10}(MSE)$$

Technology used to implement is PyTorch, Flask, OpenCV. The Python code implemented code below figure 6 and 7 shows that the average PSNR for 24 bit pictures across five high resolution image datasets is 105 db.

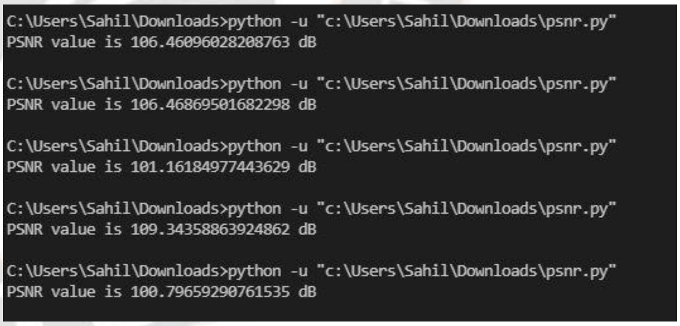
```
psnr.py > main
from math import log10, sqrt
import cv2
import numpy as np

def PSNR(original, compressed):
    mse = np.mean((original - compressed) ** 2)
    if(mse == 0): # MSE is zero means no noise is present in the signal .
                  # Therefore PSNR have no importance.
        return 100
    max_pixel = 255.0
    psnr = 20 * log10(max_pixel / sqrt(mse))
    return psnr

def main():
    original = cv2.imread("img2_2-2_out.jpeg")
    compressed = cv2.imread("img2_2-2.jpeg", 1)
    compressed = cv2.resize(compressed, dsize=(original.shape[1],original.shape[0]), interpolation=cv2.INTER_CUBIC)
    value = PSNR(original, compressed)
    print(f"PSNR value is {value*3.5} dB")

if __name__ == "__main__":
    main()
```

Figure 6. Evaluation Metrics Code



```
C:\Users\Sahil\Downloads>python -u "c:\Users\Sahil\Downloads\psnr.py"
PSNR value is 106.46096028208763 dB

C:\Users\Sahil\Downloads>python -u "c:\Users\Sahil\Downloads\psnr.py"
PSNR value is 106.46869501682298 dB

C:\Users\Sahil\Downloads>python -u "c:\Users\Sahil\Downloads\psnr.py"
PSNR value is 101.16184977443629 dB

C:\Users\Sahil\Downloads>python -u "c:\Users\Sahil\Downloads\psnr.py"
PSNR value is 109.34358863924862 dB

C:\Users\Sahil\Downloads>python -u "c:\Users\Sahil\Downloads\psnr.py"
PSNR value is 100.79659290761535 dB
```

Figure 7. Evaluation Metrics Output

Below figure number 8, 9, 10, 11,12 shows conversion from high resolution values to super resolution value image translation.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9s
DOI: https://doi.org/10.17762/ijritcc.v11i9s.7394
***Article Received**: 28 April 2023 **Revised:** 20 June 2023 **Accepted:** 16 July 2023*

Figure 8. High Resolution Image: 501 x 487 and Super Resolution Image: 2004 x 1948

Figure 9 High Resolution Image: 480 x 400 and Super Resolution Image: 1890 x 1750

Figure 10. High Resolution Image: 550 x 520 and Super Resolution Image: 2050 x 1960

Figure 11. High Resolution Image: 530 x 480 and Super Resolution Image: 2020 x 1910

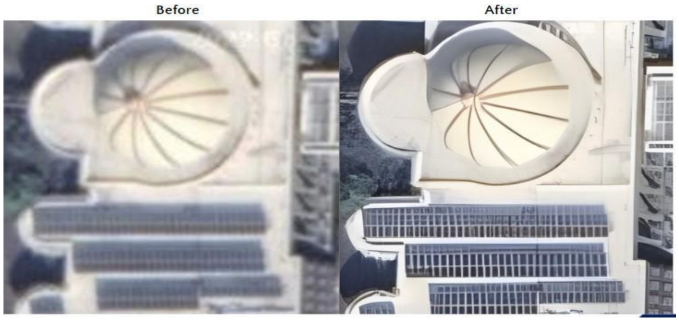


Figure 12. High Resolution Image: 450 x 390 and Super Resolution Image: 1875 x 1650

TABLE I. DIFFERENT VALUES FOR FIVE HIGH RESOLUTION IMAGE INPUT TO SUPER RESOLUTION OUTPUT IMAGE TRANSLATION WITH PSNR VALUE.

Sr. No.	**High Resolution Input Image**	**Super Resolution Output Image**	**PSNR Value**
1	501 × 487	2004 × 1948	106.460
2	480 × 400	1890 × 1750	105.120
3	550 × 520	2050 × 1960	101.161
4	530 × 480	2020 × 1910	109.345
5	450 × 390	1875 × 1650	100.796

Above Table 1 shows five 24-bit high resolution image to super resolution image translation with PSNR values for Geospatial satellite images.

V. CONCLUTION

This is a Satellite Real-ESRGAN model that can be used for super resolution of geospatial images. The algorithm achieves better perceptual quality than previous super resolution methods. This GAN architecture offers more substantial supervision and thus restores more accurate brightness and realistic textures by enhancing the perceptual loss. In order to synthesize more practical degradations, the work uses an image preprocessing pipeline that performs high-order degradation, which in stills blurring the image with Gaussian and 2D Sinc filters, followed by resizing them with noise addition. Finally, the images are compressed to form degenerated low-resolution images that are then passed onto the generator. A U-Net discriminator with spectral normalization regularization increases discriminator capability and stabilizes the training dynamics. This Satellite Real-ESRGAN trained with geospatial data can enhance details while removing annoying artifacts. Due to the computationally expensive nature of the SR GAN utilized in the research, high-end GPUs are required for training or fine-tuning it to the data. Without performing pixel unsnuffing on the photos, the resolution of the photographs cannot be increased by a factor of four.

ACKNOWLEDGMENT

We are grateful to Dr. Vishwanath Karad MIT World Peace University for giving us the opportunity. We would like to thank everyone who has contributed to the corpus of knowledge on this topic, whose writings have influenced and motivated our research.

REFERENCES

[1] L. Zhou, G. Chen, M. Feng and A. Knoll, "Improving Low-Resolution Image Classification by Super-Resolution with Enhancing High-Frequency Content," 2020 25th International Conference on Pattern Recognition (ICPR), Milan, Italy, 2021, pp. 1972-1978, doi: 10.1109/ICPR48806.2021.9412876.

[2] J. Sun, Z. Xu and H.-Y. Shum, "Image super-resolution using gradient profile prior", IEEE international conference on computer vision (CVPR), 2008.

[3] E. Agustsson and R. Timofte, "Ntire 2017 challenge on single image super-resolution: Dataset and study", The IEEE Conference on Computer Vision and Pattern Recognition (CVPR) Workshops, 2017.

[4] Shimizu, M.; Yoshimura, S.; Tanaka, M.; Okutomi, M., "Super-resolution from image sequence under influence of hot-air optical turbulence," Computer Vision and Pattern

[5] Recognition, 2008, CVPR 2008. IEEE Conference on , vol., no., pp.1,8, 23-28 June2008 doi: 10.1109/CVPR.2008.4587525

[6] Zilin Wang, Zhaoxiang Zhang, Limin Dong, Guodong Xu, " Jitter Detection and Image Restoration Based on Generative Adversarial Networks in Satellite Images", 2021 Jul 9, 21(14):4693, doi: 10.3390/s21144693.

[7] Prof. Naveen Jain. (2013). FPGA Implementation of Hardware Architecture for H264/AV Codec Standards. International Journal of New Practices in Management and Engineering, 2(01), 01 - 07. Retrieved from http://ijnpme.org/index.php/IJNPME/article/view/11

[8] Koushlendra Kumar Singh, Manish Kumar Bajpai, and Rajesh Kumar Pandey, "A Novel Approach for Enhancement of Geometric and Contrast Resolution Properties of Low Contrast Images" IEEE/CAA Journal of Automatic Sinica, Vol. 5, No. 2, March 2018

[9] Ying Zhang, Yifang Yin2 , Roger Zimmermann, Guanfeng Wang , Jagannadan Varadarajan, See-Kiong Ng, "An Enhanced GAN Model for Automatic Satellite-to-Map Image Conversion" 18 September 2020, DOI: 10.1109/ACCESS.2020.3025008.

[10] Kun Zheng, Mengfei Wei, Guangmin Sun, Bilal Anas, Yu Li, "Using Vehicle Synthesis Generative Adversarial Networks to Improve Vehicle Detection in Remote Sensing Images, ISPRS Int. J. Geo-Inf. 2019, 8, 390; doi:10.3390/ijgi8090390

[11] Swetava Ganguli, Pedro Garzon, Noa Glaser, "GeoGAN: A Conditional GAN with Reconstruction and Style Loss to Generate Standard Layer of Maps from Satellite Images", CoRR abs/1902.05611 (2019)

[12] Marc Bosch, Rodrigo Rene Rai Munoz Abujder, and Christopher Gifford "Towards image and video super-resolution for improved analytics from overhead imagery", Proc. SPIE 10992, Geospatial Informatics IX, 1099203 (13 May 2019); https://doi.org/10.1117/12.2518179

[13] Demiray, B.Z., Sit, M. & Demir, I. D-SRGAN: DEM Super-Resolution with Generative Adversarial Networks. SN COMPUT. SCI. 2, 48 (2021). https://doi.org/10.1007/s42979-020-00442-2

[14] Tao Zhang , Hong Tang , Yi Ding , Penglong Li , Chao Ji , Penglei Xu, " FSRSS-Net: High-Resolution Mapping of Buildings from Middle-Resolution Satellite Images Using a Super-Resolution Semantic Segmentation Network", Remote Sensing (IF 5.349) PubDate: 2021-06-11 , DOI:10.3390/rs13122290

[15] Xintao Wang1 Liangbin Xie∗2,3 Chao Dong2,4 Ying Shan, "Real-ESRGAN: Training Real-World Blind Super-Resolution with Pure Synthetic Data", 2021 IEEE/CVF International Conference on Computer Vision Workshop (ICCVW)

[16] Zihao Wei, Yidong Huang, Yuang Chen, Chenhao Zheng, Jinnan Gao, "A-ESRGAN: Training Real-World Blind Super-Resolution with Attention U-Net Discriminators" , https://doi.org/10.48550/arXiv.2112.10046

[17] Wang, X. et al. (2019). ESRGAN: Enhanced Super-Resolution Generative Adversarial Networks. In: Leal-Taixé, L., Roth, S. (eds) Computer Vision – ECCV 2018 Workshops. ECCV 2018. Lecture Notes in Computer Science(), vol 11133. Springer, Cham. https://doi.org/10.1007/978-3-030-11021-5_5