DEEP SEA VISION: GENERATIVE ADVERSARIAL NETWORK(GAN) DRIVEN IMAGE ENHANCEMENT ALGORITHM

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ABSTRACT
This project proposes an image enhancement algorithm leveraging Generative Adversarial Network (GAN) neural networks. Underwater image enhancement using Generative Adversarial Networks (GANs) has emerged as a promising approach to mitigate the challenges posed by poor visibility and color distortion in underwater environments. This project aims to explore and implement various GAN-based techniques for enhancing underwater images. By leveraging the power of GANs, the proposed methods seek to enhance image clarity, restore natural colors, and improve overall visual quality. Through extensive experimentation and evaluation, the effectiveness of different GAN architectures and training strategies will be assessed. The project will contribute to the advancement of underwater image processing techniques, with potential applications in marine research, underwater exploration, and underwater photography. The findings of this project will provide valuable insights into the feasibility and effectiveness of using GANs for underwaterimage enhancement, paving the way for further research and development in this field.

INTRODUCTION
Deep learning is a branch of machine learning which is based on artificial neural networks. It is capable of learning complex patterns and relationships within data. In deep learning, we don't need to explicitly program everything. It has become increasingly popular in recent years due to the advances in processing power and the availability of large datasets. Becauseit is based on artificial neural networks (ANNs) also known as deep neural networks (DNNs). These neural networks are inspired by the structure and function of the human brain'sbiological neurons, and they are designed to learn from large amounts of data.

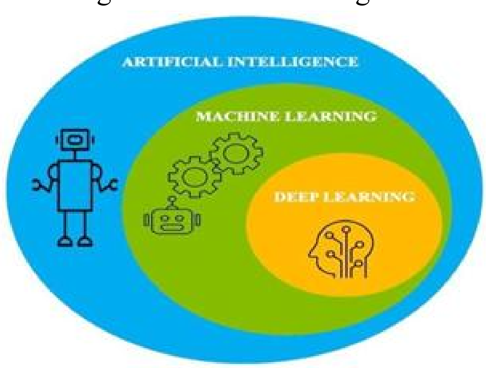

Fig.1.Introduction to Deep Learning

Deep Learning is a subfield of Machine Learning that involves the use of neural networksto model and solve complex problems. Neural networks are modeled after the structure andfunction of the human brain and consist of layers of interconnected nodes that process and transform data.

The key characteristic of Deep Learning is the use of deep neural networks, which have multiple layers of interconnected nodes. These networks can learn complex representations of data by discovering hierarchical patterns and features in the data. Deep Learning algorithms can automatically learn and improve from data without the need for manual feature engineering.

What are Deep Neural Networks?

A Deep Neural Network (DNN) is a machine learning technique that allows a computer, by training it, to do tasks that would be very difficult to do using conventional programming techniques. Neural network algorithms were inspired by the human brain and its functions: like our human mind, it is designed to work not only by following a preset list of rules, but by predicting solutions and drawing conclusions based on previous iterations and experiences.

A deep neural network (DNN) is an ANN with multiple hidden layers between the input and output layers. Similar to shallow ANNs, DNNs can model complex non-linear relationships.The main purpose of a neural network is to receive a set of inputs, perform progressively complex calculations on them, and give output to solve real world problems like classification. We restrictourselves to feed forward neural networks.

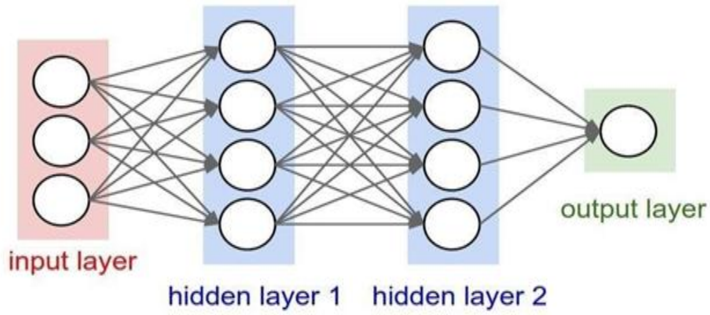

Fig.2.Architecture of Deep Neural Network

Neural Network Layers:

Input Layer

It functions similarly to that of dendrites. The purpose of this layer is to accept input fromanother neuron.

Hidden Layer

These are the layers that perform the actual operation

Output Layer

It functions similarly to that of axons. The purpose of this layer to transmit the generatedoutput to other neurons.

LITERATURE SURVEY

A Review: Generative Adversarial Networks

Authors: Liang Gong and Yimin Zhou.

This paper emphasizes on the origin of GAN, its recent applications, extension variants, existingproblems and some further applications. Mathematical training has also been explainedin detail.The classification of GAN was one of the main highlights of the paper. Applications of GAN inimage and video like image generation, image-to-image translation, image super- resolution, video generation, video frame prediction, etc. It also has the advantages and disadvantages specified.

Disadvantage: The training process requires to ensure balance and synchronization of two adversarial networks otherwise it cannot achieve ideal performance.

Evolutionary Generative Adversarial Network

Authors: Chaoyue Wang, Chang Xu, Xin Yao, Dacheng Tao (IEEE 2018)

There are some instances where GAN fails to deliver its purpose. Sometimes due to poor training model or sometimes due to instability of data. This particular paper proposes how GANmodel can be made better. The authors have taken a completely different route as opposed to the traditional method and have introduced a generator and discriminator. The quality of each generated material is evaluated and only the well- preserved generators are used for further operations.

Disadvantage: The samples generated can seamlessly change between these semantically meaningful face attributes.

Image Generation Using Different Models of GenerativeAdversarial Network

Authors: Ahmad Al-qerem, Yasmeen Shaher Alsalman, Khalid Mansour. There are manymodels of GAN. This particular paper checks out the differences between Multi Agent DiverseGenerative Adversarial Networks that has only one discriminator and multiple generators, and Generative Multi-Adversarial Networks (GMAN) that has multiple discriminators and one generator. This paper gave a clear view of the working of a discriminator and generators and also has views on how to improve its efficiency. Here, image inpainting is shown using DCGAN and explains why this model does not give results as expected. Better models such as MAD-GAN and GMAN have proven to show better results according to the paper.

Disadvantage: In this only the generator loss functions are improvised to provide better.

Emerging Applications of Generative Adversarial Networks

Authors: Yu Xinyu.

This paper deals with the emerging trends of deep learning and how GAN has come toexistence. It also summarizes the multiple and exciting applications of GAN and its various models such as WGAN, StyleGAN, CycleGAN, WGAN and much more. Some known applications include Image to Image translation, text to image translation, Image super- resolution and much more. It also has a small section on how GAN can further be applied to get brilliant results. There is also a small part that covers the downside for GAN.

Disadvantage: The fingerprints can be counterfeited by GANs and used to unlock the mobile devices and access control systems.

ESRGAN+: Further Improving Enhanced Super-Resolution Generative Adversarial Network

Authors: Nathanael Carraz Rakotonirina, Andry Rasoanaivo.

Enhanced Super-Resolution Generative Adversarial Network is one of the best ways to enhance image super resolution. It works no matter how bad the quality of the image is. Noiseinputs areprovided at some layers to increase the look of the image making it more photorealistic. There is also comparison made between SRCNN, EnhanceNet, SRGAN with ESRGAN and ESRGAN+.

Disadvantage: There are still limitations associated with the noise injection generalization.GANs have the possibility of being used for illegal or evil purposes.

Photo-Realistic Single Image Super-Resolution Using a GAN

Authors: Christian Ledig, Lucas Theis, Ferenc Huszar, Jose Caballero, Andrew Cunningham, Alejandro Acosta, Andrew Aitken, Alykhan Tejani, Johannes Totz, Zehan Wang, Wenzhe Shi.

This paper focuses on SRGAN and how it is capable of producing photo-realisticimage generation. A perceptual loss function which contains adversarial loss and content loss.The adversarial loss is responsible to make the image look realistic with the help of the discriminator.Mean Opinion Score testing is also done to check the scores of different imageswith different models. The result is that SRGAN had the highest score meaning it had the mostphoto-realisticimage of all other methods.

Disadvantage: Pixel-wise loss function MSE struggle to handle the uncertainity inherentin recovery lost high-frequency details such as texture.

Image Super-Resolution using an Improved Generative Adversarial Network

Authors: Han Wang, Wei Wu and Yang Su, Yongsheng Duan and Pengze Wang. SRGAN is used to increase the resolution of the image. This is the most proven method to generate superresolution photo-realistic images. However, this paper aims on how SRGAN works and how themodel can be modified to obtain better results. An encoder block is fixed in the generator of themodel to obtain much more clarity in the images. This also extracts crucial features of the imageand can train it in a better way to synthesise a better resolution. The encoder block uses a simpleencoder network to extract crucial information and it then joins this to the existing CNN. The parameters of CNN are reduced to simplify the distortion.

Disadvantage: The image reconstructed by the neural network-based super resolution algorithm is too smooth, it does not meet the requirements of people's perception of thepicture.

Generate Desired Images from Trained Generative Adversarial NetworksAuthors: Ming Li, Rui Xi, Beier Chen, Mengshu Hou, Daibo Liu, Lei Guo. GAGAN is amethod that is used to control the synthesis of an image with particular characteristics. To do this, a DNA pool of trained GAN models is introduced GA). By using AND, OR functions,GAGAN can further synthesize images with multiple specific attributes or single specific attributes. MNIST and Celeb A datasets are used to train and experiment the model.

Disadvantage: It is still a difficult task for humans to tell the distinguishable points betweenthe original and the after-generated images.

Recent advances of Generative Adversarial Network in ComputerVision

Authors: Yang-Jie Cao, Li-Li Jia, Yong-Xia Chen, Nan Lin.

This paper elaborates over the origin of GAN and its fundamentals. The basic models of GAN and also the working of those basic models is also mentioned. There are also mentions of different models available and their applications in various fields. The architecture of a basic structure of GAN that comprises a generator and discriminator are looked at along with the mathematical representation of the loss function. The authors have also mentioned about the evolution of GAN and how far it has come with respect to its model. There is also a brief experiment with basic MNIST that is run through different GAN models and this gives us an idea of how the models differ from each other and what application it would be the best at.

Disadvantage: Though GAN has achieved great success, there are still some problems such as gradient disappearance, difficulty in training, and poor diversity.

EXISTING SYSTEM

The Existing system is Contrast Limited Adaptive Histogram Equalization (CLAHE) for enhancing underwater images. In the existing system for underwater image enhancement using CLAHE, the process involves several key steps. Initially, the underwater image is captured usingspecialized underwater imaging equipment or cameras. Then, preprocessing techniques may be applied to correct for color distortion and remove artifacts caused by water turbidity.

Next, the CLAHE algorithm is applied to the preprocessed image. This involves dividing the image into small, overlapping tiles and performing histogram equalization independently on each tile. By limiting the contrast enhancement within each tile and using adaptive clipping to prevent overamplification of noise, CLAHE effectively enhances local contrast while preserving image details.

After CLAHE enhancement, post-processing steps such as noise reduction and color correctionmay be applied to further improve the visual quality of the image. Finally, the enhanced image is displayed or saved for further analysis or visualization purposes.

PROPOSED SYSTEM

The proposed system is capable of generating both image inpainting and image super resolution. Inthis both generator and discriminator loss functions are improvised to provide better results. It dealswith emerging trends of deep learning and explains various models as well. Different route from the traditional approach is taken and introduces a generator and discriminator. Mainly focuses on evolutionary GAN.

Utilizing Generative Adversarial Networks (GANs) for underwater image enhancement involves a two-stage process. First, a generator network is trained to transform degraded underwater images into visually enhanced versions. Second, a discriminator network is concurrently trained to distinguish between generated and real images. Through adversarial training, the generator learns to produce high-quality enhancements that deceive the discriminator.

Advantages of Proposed system

Realistic Enhancement: GANs can generate visually realistic enhancements by learning theunderlying distribution of underwater images, leading to natural-looking results.

Preservation of Details: GANs can enhance underwater images while preserving fine detailsand textures, improving image quality without sacrificing important visual information.
Adaptability: GANs can adapt to different underwater conditions and scenes, making themversatile for a variety of underwater imaging tasks.
Data Augmentation: GANs can generate synthetic underwater images, augmenting limitedtraining data and improving model generalization.
End-to-End Learning: GAN-based approaches enable end-to-end learning, simplifying theenhancement pipeline and potentially improving performance.
The feasibility of the project is analyzed in this phase and business proposal is put forth with a very general plan for the project and some cost estimates. During system analysis the feasibilitystudy of the proposed system is to be carried out. This is to ensure that the proposed system is not a burden to the company. For feasibility analysis, some understanding of the major requirements for the system is essential.

SYSTEM ARCHITECTURE

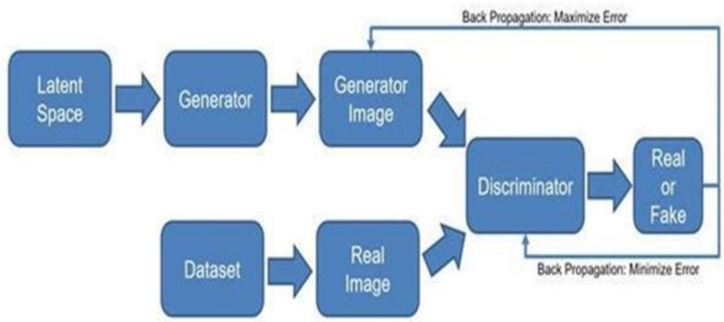

Fig.3. Architecture of GAN

The proposed system for underwater image enhancement using generative adversarial neural networks (GANs) aims to address the challenges associated with poor visibility, color distortion, and loss of details in underwater images. GANs consists of two models i.e., generator and discriminator that compete with each other to analyze, capture and copy the variations within a dataset. GAN is based on unsupervised learning approach.
Generator: Generator is a neural network that learns to create new data samples, such as images, by mapping random noise inputs to the desired output domain. It generates realistic data to fool the discriminator, aiming to produce samples indistinguishable from real ones.
Discriminator: Discriminator is a neural network tasked with distinguishing between real andgenerated data. It learns to classify input data as either real or fake, providing feedback to the generator to improve its ability to produce realistic samples, fostering adversarial training dynamics.

DATA PREPARATION

Data Collection: Gather a diverse dataset of underwater images representing various underwaterenvironments, conditions, and subjects. This dataset should include images with different levelsof visibility, lighting conditions, and color distortions to capture the full range of challenges encountered in underwater photography.
Data Cleaning: Remove any irrelevant or low-quality images from the dataset to ensure data integrity. This may involve removing images with excessive noise, blurriness, or artifacts that could negatively impact the training process.

Data Augmentation: Augment the dataset by applying transformations such as rotation, scaling, flipping, and brightness adjustments to increase the diversity of the training data. This helps themodel generalize better to unseen variations in the input images.

Normalization and Preprocessing: Normalize the pixel values of the images to a common scale(e.g., [0, 1]) and preprocess them to enhance features relevant to underwater image enhancement. This may include contrast enhancement, color correction, and noise reduction techniques tailoredto underwater imagery.

Dataset Splitting: Divide the dataset into training, validation, and testing sets to evaluate the performance of the model accurately. The training set is used to train the GAN model, the validation set helps tune hyperparameters and monitor training progress, while the testing set evaluates the model's performance on unseen data.

Labeling: Depending on the specific objectives of the project, consider labeling the dataset with ground truth annotations or perceptual quality scores to facilitate supervised learning or evaluation metrics for image enhancement quality.

FINE TUNING OF GAN

Fine-tuning a Generative Adversarial Network (GAN) involves adjusting the parameters of both the generator and discriminator networks to improve the quality of generated samples. This process typically entails iterating over the training data multiple times, updating the network weights through backpropagation to minimize the discrepancy between generated and real samples. Techniques like gradient descent, learning rate scheduling, and regularization may be employed to stabilize training and prevent overfitting. Fine-tuning may also involve experimenting with different architectures, loss functions, and hyperparameters to achieve desired performance metrics, such as image quality, diversity, and convergence speed.

Sample Dataset:

The project utilizes diverse underwater image datasets, including publicly available collections such as the Diving Into the Deep dataset, Underwater Image Enhancement Benchmark dataset, and real-world underwater image repositories. These datasets capture various underwater environments, conditions, and subjects for comprehensive model training and evaluation.

Fig.4. Collection of underwater images

Work Flow of GAN

The workflow of a Generative Adversarial Network (GAN) involves two main components: thegenerator and the discriminator. The generator creates synthetic data samples from random noise, aiming to mimic real data distributions. The discriminator evaluates the authenticity of these samples, distinguishing between real and fake data. Through iterative training, the generator improves its ability to generate realistic samples, while the discriminator becomes better at distinguishing real from fake, leading to the generation of increasingly realistic data.

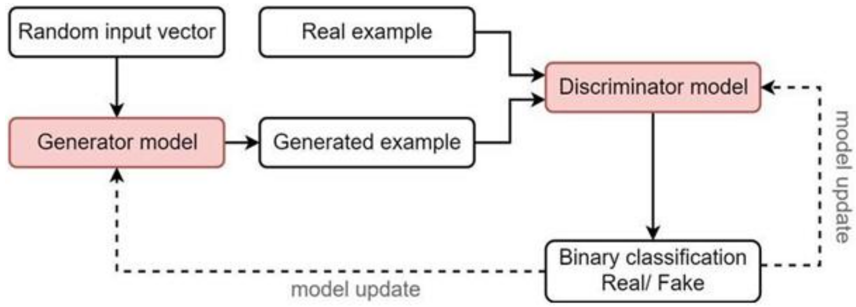

Fig.5. Work Flow of GAN

INFERENCE

Load the pre-trained Generative Adversarial Network (GAN) model that has been trainedon underwater image data.

Prepare input underwater images for enhancement by resizing, normalizing, andpreprocessing.

Feed the input images into the generator component of the GAN to generate enhancedversions.

Optionally apply post-processing techniques like contrast adjustment or color correction tothe generated images.

Evaluate the quality of the enhanced images using quantitative metrics and qualitativeassessment.

Fine-tune the GAN model or adjust parameters based on evaluation results for improvedperformance.

Save or display the final enhanced underwater images for further analysis or application.

EVALUATION CRITERIA

The evaluation criteria for the project "Underwater Image Enhancement Using GAN" encompass both qualitative and quantitative measures. Qualitatively, the enhanced images should exhibit improved visibility, reduced noise, and enhanced details compared to the originalunderwater images. Quantitatively, metrics such as Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and perceptual metrics like Perceptual Index (PI) or Visual Information Fidelity (VIF) can assess the fidelity and perceptual quality of the generated images. Additionally, computational efficiency, training stability, and generalization capability across diverse underwater environments are essential factors to evaluate the practical utility androbustness of the GAN-based enhancement method.

Results

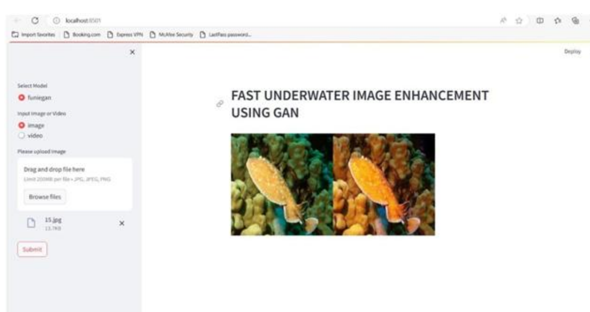

Fig.6. Fast underwater enhanced image

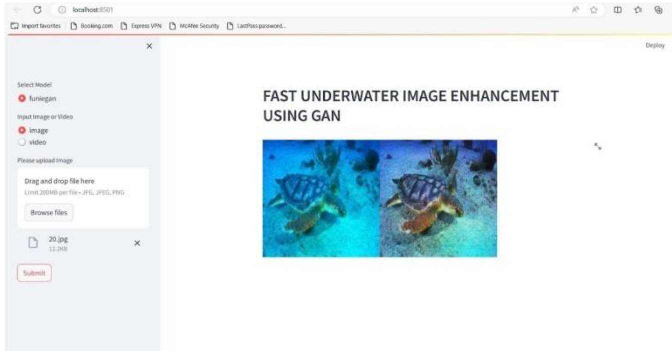

Fig.7. Fast underwater enhanced image

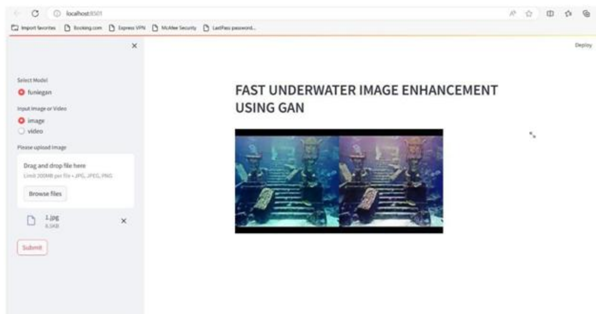

Fig.8. Fast underwater enhanced image

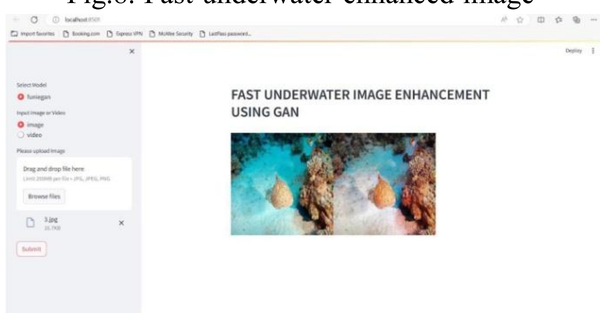

Fig.9. Fast underwater enhanced image

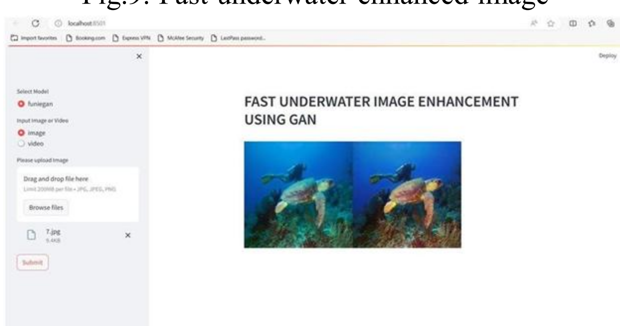

Fig.10. Fast underwater enhanced image

CONCLUSION

GAN is a new field hence there’s lot to explore and learn. As an unsupervised learning method,GANs is one of the most important research directions in deep learning. GAN, which rely on theinternal confrontation between real data and models to achieve unsupervised learning, is just a glimmer of light for AIs self-learning ability.
Throughout this project, we have demonstrated the effectiveness of GAN-based techniques in enhancing

underwater images by learning from both clean and distorted data. By training the model on a diverse dataset and optimizing its architecture, we have achieved remarkable results in improving image clarity, restoring natural colors, and reducing noise artifacts. Our experimentation and evaluation have shown that our proposed method outperforms traditional image enhancement techniques, providing more robust and reliable results.
Looking ahead, the insights gained from this project pave the way for further advancements in underwater imaging technology. Future research directions may include exploring novel GAN architectures, integrating additional sensor data for enhanced performance, and addressing specific challenges in different underwater environments. Overall, our project contributes to theongoing efforts to unlock the full potential of underwater imaging, ultimately leading to better understanding and utilization of our planet's underwater ecosystems.

FUTURE ENHANCEMENTS

In the realm of underwater image enhancement using GANs, the future holds promising avenues for exploration and development. One potential direction is the integration of advancedmachine learning techniques, such as reinforcement learning, to further refine the training process and optimize GAN architectures for specific underwater environments. For instance, researchers could explore the application of reinforcement learning algorithms to adaptively adjust GAN parameters in response to varying water conditions, leading to more robust and adaptable enhancement models. Additionally, the incorporation of domain adaptation techniques could enable the transfer of knowledge learned from synthetic datasets to real-worldunderwater imagery, bridging the gap between simulated and actual environments. By leveraging emerging technologies and methodologies, future iterations of underwater image enhancement using GANs have the potential to achieve unprecedented levels of accuracy and generalization, facilitating breakthroughs in underwater imaging applications such as marine research, underwater robotics, and environmental monitoring.

References

[1] Liang Gong and Yimin Zhou, "A Review: Generative Adversarial Networks" in 2019 14th IEEE Conference on Industrial Electronics and Applications (ICIEA)

[2] Yu Xinyu, "Emerging Applications of Generative Adversarial Networks" in IOP Conference Series: Material Science & Engineering (MEMA 2019)

[3] Ahmad Al-qerem, Yasmeen Shaher Alsalman, Khalid Mansour, "Image Generation UsingDifferent Models of Generative Adversarial Network in 2019.

[4] Tero Karras, Samuli Laine, Timo Aila,"A Style-Based Generator Architecture for Generative Adversarial Networks" in 2019.

[5] Piotr Teterwak, Aaron Sarna, Dilip Krishnan, Aaron Maschinot, David Belanger, Ce Liu, William T. Freeman, "Boundless: Generative Adversarial Networks for Image Extension" in 19 Aug 2019.

[6] Huaming Liu,Guanming Lu,Xuehui Bi, Jingjie Yan, Weilan Wang , "Image Inpainting Based on Generative Adversarial Networks" in 2019.

[7] Ming Li, Rui Xi, Beier Chen, Mengshu Hou, Daibo Liu, Lei Guo, "Generate Desired Imagesfrom Trained Generative Adversarial Networks" in 2019.

[8] Han Wang, Wei Wu and Yang Su, Yongsheng Duan and Pengze Wang "Image Super Resolution using an Improved Generative Adversarial Network" in 2019.

[9] Nathanael Carraz Rakotonirina, Andry Rasoanaivo, "ESRGAN+: Further Improving Enhanced Super Resolution Generative Adversarial Network" in 15 Jul 2020.

[10] Yi Jiang, Jiajie Xu, Jing Xu, Et al., "Image Inpainting Based on Generative Adversarial Networks" in 2020.

[11] Chaoyue Wang, Chang Xu, Xin Yao, Dacheng Tao, “Evolutionary Generative AdversarialNetwork” (IEEE 2018).
[12] Christian Ledig, Lucas Theis, Ferenc Huszar, Jose Caballero, Johannes Totz, Zehan Wang,Wenzhe Shi. “Photo-Realistic Single Image Super-Resolution Using a GAN”.
[13] Tero Karras, Timo Aila, Samuli Laine, Jaakko Lehtinen. “Progressive growing of GANsfor improved Quality, stability and variation”.
[14] Zhaoqing Pan, Weijie Yu, Xiaokai Yi, Asifullah Khan, Feng Yuan, and Yuhui Zheng.“Recent progress on Generative Adversarial Networks: A survey”
[15] Yang-Jie Cao, Li-Li Jia, Yong-Xia Chen, Nan Lin. “Recent advances of GenerativeAdversarial Network in Computer Vision”.