A Survey on the Applications of Generative Adversarial Networks

Ashish Roy[1], Dr. B. G. Prasad[2]

Department of Computer Science & Engineering, B.M.S. College of Engineering, Bengaluru, India
ashishroytech[at]gmail.com

Department of Computer Science & Engineering, B.M.S. College of Engineering, Bengaluru, India
bgprasad.cse[at]bmsce.ac.in

Abstract: ***Generative Adversarial Networks are computational structures consisting of two neural networks, i.e., a generator network and a discriminator network. The networks compete against each other to create new and synthetic data instances (thus the term "adversarial"). The Generator network takes random noise as input, transforms and reshapes it into a recognizable structure using a differential function. The generator's output appears to be an actual data point. When the generator network runs with various input noise levels, it creates multiple realistic output data samples. The purpose of these created data samples is to be representative of the real-world data distribution. In addition, GANs employ an approximation in which the generator network is guided by a second network called the Discriminator to produce samples from the probability distribution of input data. The Discriminator is a standard neural network classifier that separates the genuine examples from the generator's bogus samples. Thus, it helps in identifying whether the given image is real or fake. Some of the GAN applications discovered are 3D object production, image processing, pandemics, face detection, medicine, and traffic control. This paper provides a systematic study and analysis of the recent GAN model and its applications.***

Keywords: Generative Adversarial Networks, Conditional GAN's, Deep convolutional neural network.

1. Introduction

For years, scientists have researched natural image generation in-depth, and until 2014, advances in deep learning did not allow the creation of image samples and interpolations with extremely high visual accuracy. The Generative Adversarial Network is the primary model that has made it possible. A generator model and a discriminator model are the two models that make up the concept. The generator model must create new reasonable instances that are distinct from the existing cases in the dataset [1]. The discriminator's model identifies a specific image as accurate (taken from the dataset) or false (generated). The network is guided in a zero-sum or adversarial way, with the discriminator improving at the expense of the generator's lower potential and vice versa. For image synthesis, GANs are effective, generating new image examples for a target dataset. Additional information is available in some datasets, such as a class mark, and it is preferable to use it. A GAN model has the drawback of being able to produce a random image from the domain. GAN employs a supervised learning approach that includes two primary models: the generator and discriminator models. The discriminator model seeks to classify examples as true or fake, whereas the generator model strives to generate new examples. In machine learning, generative modeling is an unsupervised learning approach that incorporates a supervised loss into the learning process.

It entails automatically finding and learning regularities or patterns in input data such that the model may be used to construct or generate new examples from the original dataset.

GANs are a dynamic and fast-developing field that fulfills the guarantee of generative models by generating accurate illustrations in a variety of application domains, particularly in image translation tasks like converting winter to summer or night to day pictures, and in developing realistic photos which even humans can't tell are fake or not [2]. The created images have a relationship with points in the latent space, but it's intricate and challenging to trace. A GAN can also be trained to condition the classmark on both the generator and discriminator models, allowing for creating images of a specific category or class mark when the trained generator model is used to develop ideas in the domain stand-alone model.

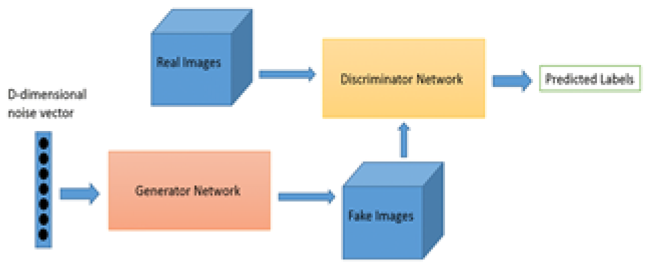

Figure 1: Architecture of GAN

The architecture of a typical GAN is depicted in Figure 1. G (Generative Network) defines a probability distribution pg as the distribution of samples G(z), given a distribution z~pz. A GAN's goal is to learn the generator's distribution pg, which is similar to the real data distribution pr. A joint loss function for D (Discriminator Network) and G (Generative Network) is used to optimize a GAN (Eq-1).

$$\min_{G}\max_{D} E_{x\sim pr} \log[D(x)] + E_{z\sim pz} \log[1 - D(G(z))] \qquad \text{Eq-1}$$

The limitation of GAN is taken care of by Conditional gans.

The definition of plain GANs is expanded by conditional GANs (cGAN's), allowing us to control the output of the generator network.

The following section gives an overview of applications in the domain of Generative Adversarial Networks, with more emphasis on visual synthesis applications and their algorithms. It covers several essential techniques for stabilizing GAN preparation, which is notoriously difficult [15].

2. Literature Survey

2.1 Face Recognition

The first successful work in computer vision was developing an algorithm that could detect a human face [1]. Viola P. and Jones M. developed this algorithm, hence the name Viola-Jones algorithm. Some prominent features mapped to the human face are similar to the Haar filters, such as eyes, nose, cheeks, etc. Windows of size 24*24 are used to look at the input image to identify Haar features. There was a 160,000+ Haar filter calculation for each window.

Adaboost was used to eliminate some dispensable features; this algorithm used 7000 feature calculations for each window. This algorithm was further optimized by dividing the feature parts called Cascading [2]. Even after using Adaboost, the Integral Image and Viola Jones cascading algorithm were not successful because it was computationally costly and slow for real-time facial detection applications. In addition, the Viola-Jones algorithm failed to classify faces from various angles. For several real-time applications, neural network creation opened the door because neural networks had the potential to self-learn without the need for any hardcoded features when trained on a collection of supervised data.

Scandrett et al. [4] compute the difference in the root mean square shape and the difference in the root mean square intensity between two faces given an aged face and a target face of the same age. Scandrett et al. [4] determine the correlation between advanced textures and all samples at the target age [3].

When they applied the methods indicated in [4] [3], they discovered that the correlation coefficient between the aged and target faces is higher than the correlation coefficient between the aged image and other faces in the target age group. The general similarity of two faces depends on the shape and metrics based on texture and does not include reliable information relevant to the similarity in age and two-faced identity. Because both metrics are heavily dependent on non-aging sorts of variations, these indicators should not be used in conjunction with face photos that show significant non-aging-related variability.

Geng et al. [5] and Lanitis et al. [6], based on two separate metrics, determine the precision of face-aging. The first relies on Mahalanobis distance, while the second is entirely predicated on the findings of facial recognition. They calculate the Mahalanobis distance between the coded representation of aged faces and the target faces in the first case. Because it is possible to build a covariance matrix that highlights the difference between id or aging, Mahalanobis distance is strongly reliant on estimating the covariance matrix for determining face-aging.

Face recognition tests were conducted by Geng et al. [5] and Lanitis et al. [6], in which they attempted to recognize faces in situations when the age of faces in test photographs differed significantly from faces of identical persons in the training set [3]. Raw or digitally aged photos of a person's face can be used for facial recognition. In such studies, when using age-progressed images, improvements in face recognition rate show an aging algorithm's potential to generate looks that maintain the source image's identical characteristics. However, evaluating face-aging accuracy based on facial recognition results is an indirect method of assessing face-aging efficiency.

In a more recent approach, face aging is carried using a recurrent framework [7]. Bypassing through the smooth intermediate faces, the face shape gradually develops, resulting in a high-quality optical flow. The synthetic faces formed from the optical flow are hence more lifelike than the one-step approaches. As a recurrent model, a two-layer GRU is utilized. The bottom layer serves as an encoder, allowing the picture to be projected into a high-dimensional space, while the top layer serves as a decoder, converting the hidden variables into an aged face. This structure is capable of modeling highly intricate dynamic appearance alterations [7]. Another method uses a single photograph of a youngster as its input. It generates a succession of age-progressed outputs between the ages of 1 and 80, taking into account a stance, expression, and illumination [8]. This method works surprisingly effectively, especially in the problematic scenario of young children, for which there have been few previous findings.

Although some retinoids can slightly reverse minor photoaging effects, face aging is often a gradual and permanent process. While everyone ages differently, aging takes on several forms and manifests itself in a variety of ways. At different ages, there are usually some overall improvements and similarities.

The most critical improvement is craniofacial growth from birth to adulthood throughout the early growth and development of the face. Overall, during craniofacial development, the face size gradually gets larger.

Figure 2: A woman's Face Ageing (Collected by Internet Image)

The above images show the variation in the face feature of the women as age progresses. With development, the forehead slopes down, shrinks, and releases gaps on the surface of the skull, while facial features like the eyes, nose, ears, and mouth expand their regions and appear to cover these interstitial spaces. Chins spread to broader areas, being more protrusive to the chin. Facial skin does not alter nearly as much as craniofacial skin.

The most significant transition is skin aging during maturity, from adulthood to old age. The alteration in form persists but less drastically, mainly due to normal skin and tissue patterns. Thus, the concepts of beauty and distinctiveness and explicit caricatures or changes based on factual knowledge of biological anthropometry are widely used to clarify and apply facial aging in perception and aesthetics (face development, growth, and aging).

2.2 Cybersecurity

Cyber-threats have become more prevalent in recent years. To avoid confidential information from being leaked and misused, organizations are implementing advanced security measures. Hackers, on the other hand, are constantly devising new ways to access and manipulate user data. Criminal activities such as blackmailing users to keep their information secret, publicly sharing data to humiliate people, and tarnishing their reputations with false photos and videos are on the rise and pose a severe threat. In addition, people are actively sharing more and more data on the internet in photographs and videos, making it a convenient source to misuse. Since the invention of GANs in 2014, one of the leading research areas for the application of GANs has been the use of technology for adversarial studies. The motivation for this is that when the feature space in which learning happens shifts, neural networks and other machine learning models, in general, perform poorly.

They can cause permanent damage to the system as well as data leakage. As a result, detecting these anomalies as soon as possible is essential. Traditional supervised approaches such as Decision Trees and Support Vector Machines (SVM) are used to distinguish normality and abnormality. It proposes an efficient GAN-based model with a specially built loss function [9]. However, abnormal status is more common than average status, resulting in decision bias in these processes. In order to deal with these kinds of situations, the generative adversarial network (GAN) has been suggested. Its strong production capacity only needs to learn the normal status distribution and recognize abnormal status by comparing it to the learned distribution.

2.3 Image Processing

For blur images, wiener filtering is used to obtain clean pictures from a hard threshold. Furthermore, these visuals are degraded to gain factors for a 3D block-matching algorithm that uses GAN training of latent clean photographs to produce clean images. The ultrasound picture resolution problem will be solved by incorporating deep learning models with GAN algorithms.

These are utilized to complete the encoding and decoding of prostate ultrasound pictures recorded regularly to create high-resolution images [11]. GAN's will build different lesion groups from a restricted sample size of each lesion after using deep convolutional GAN's generate a 3D image from a 2D image, resulting in quicker image processing [12].

When taking pictures in bad weather, such as rainstorms or snowstorms, the image quality will suffer. The researchers attempt to change conditional GAN's generative modeling capabilities by adding the restriction to eliminate the raindrop that affects image quality [13]. In addition, a convertible conditional GANSs for editing images has been created by another group of researchers [14].

By reversing the mapping of conditional generative adversarial networks, they test encoders to re-generate authentic images with complicated deterministic alterations.

This paradigm has shown to be a valuable tool for a wide range of image and video synthesis applications, allowing for whole or input-conditional visual material synthesis. In addition, it has made it possible to create photorealistic high-resolution photographs, which was previously difficult or impossible.

2.4 3-D Object Generation

3D GAN creates 3D objects in probabilistic space by combining generative adversarial networks and volume convolutional networks. Rather than employing heuristics, the model employs a three-tier adversarial theory, which allows the generator to maintain object structure while producing high-quality 3D models and generator maps from a two-dimensional to a three-dimensional object [16].

To create 3D and realistic images, a GAN that focuses on enhancing 2D monochromatic images is used [17].

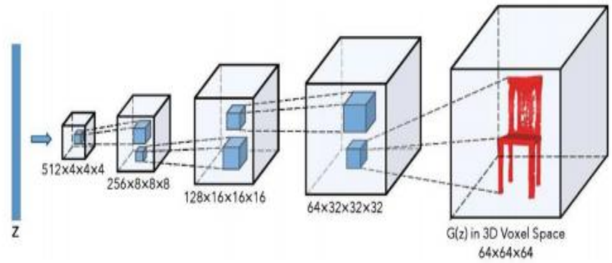

Figure 3: 3-D object Generated Image

A generative 3D model is trained with a conditional Mesh-VAE-GAN to learn about garment deformation from the SMPL body model and evaluate human movements and postures, and it is made up of a collection of people wearing garments performing 3D scans in various stances and outfits [18].

2.5 Medical Science

In the medical field, Generative Adversarial Network models are beneficial for detecting chronic diseases. Based on a generator network, the discriminator termed GAN-Poser, Jain et al. introduced a new methodology for predicting the motion of a human with 3D feedback of a human skeletal picture [19]. GAN is being used in a clinical program to help with image-to-image communication and medical picture recognition without the need for supervision [20]. It has also been proved that these networks can recognize brain PET scans for the diagnosis of Alzheimer's disease (AD) in three phases using fake medical metaphors (regular, moderate, and severe) [21].

According to the paper, any device based on a 3D conditional GAN that employs spectral normalization to stabilize feature matching parameters achieves convergence optimization. A self-contained conditional GAN outperforms standard 2D and 3D conditional GANs, enabling complex 3D profound learning-based neuroimaging synthesis.

Compared to more typical SDM generation approaches, machine learning, medical imaging, and deep learning are employed to construct a signed distance map for the cochlea based on four input parameters that reduce computation time by 60 times. [22]

An upgraded Generative Adversarial Network is a deep Super-Resolution GAN that generates Alzheimer's disease picture stages for three separate sets of brain standard control, moderate cognitive dysfunction, and disease[23]. Image mixture accuracy is often improved using a Bayesian conditional GAN with excessive function dropouts. However, compared to conventional Bayesian neural networks, the Bayesian network created uncertainty in feature interpretation when used on samples of brain tumor datasets with over 100 examples [23].

2.6 General Applications

There is a wide range of applications in multiple domains, including cross-age face recognition, locating missing kids, and entertainment. It's feasible to roughly divide traditional facial aging approaches into prototype and modeling categories. Parametric models are used in modeling techniques to predict the aging processes of a given individual's muscles, skin, and skull. On the Contrary, in predefined age groups, prototyping methods estimate average faces. It was also utilized to transform an input facial image into the appropriate age group.

In other applications, The GAN network enhances astronomical imagery, predicts and simulates gravitational sensing for the investigation of dark matter, and models dispersion in any space direction [24]. According to the researchers, when an image is set forth on a land vehicle from radar, i.e., FMCW radar, the promise of vehicle localization is realized. A map is constructed to evaluate climatic variations such as lightning and thunder, consistent with sensor nature.

The climate fluctuations and lighting compatible with sensor nature have been analyzed using a map [25]. In addition, GANs projected a more accurate approach to modeling high-energy jet production, decreasing the cost of particle physics simulations [26]. Despite accepting any image as input for GAN classification, the discriminator network is adjusted to indicate the point of the class of any picture.

It is possible to allow for the stabilization of training and the production of broad excellence photographs. Fs-GANs have been used in the design industry to create fictitious models without hiring a photographer or makeup artist, reducing studio costs [27]. Fashion advertising agencies are using GANs to increase the number of people who look like models. GAN can be used to produce landscapes, portraits, and album covers which can be utilized to develop games by scaling the texture resolution in 2D and generating higher qualities [28].

The training process is further downscaled to meet the game's native resolution. Anti-aliasing outputs are comparable to super sampling outputs. When correctly trained, such networks can create a clearer and sharper image with significant quality gains over the original. The photos were made to preserve the original degree of detail and color. Among the various GAN applications accessible are speech to video prediction, image creation, imagining weather changes, motion video capture, face feature aging, photo blending, etc.

The following Table 1 shows an overview of applications in the field of Generative Adversarial Networks along with the GAN models which were used in different domains. Each application has their own pros and cons which changes from domain to domain. In some or another way, each GAN model tries to cover up the cons of the other models.

Table 1: Different GAN Applications and their Models

Application	GAN Model	Pros
Image Recognition	C-GAN (Controllable GAN) [29]	Face Synthesis of Cross-Domain
	Dual-Agent GAN (DA-GAN) [30]	Face Recognition with No Constraints
Cyber Security	GAN [31]	Intrusion detection GAN based system
	GAN [32]	Cyber Intrusion GAN based detection
Image Processing	DNN-GAN (Deep Neural Network-based GAN) [33]	Image transformation
	Dual GAN [34]	High-resolution images Recovery
	Conventional GAN [35]	Scene generation with Semantic guidance
3-D Object Generation	GAN Point encoder [36]	Unstructured data is processed without being labeled.
Medical Science	GAN poser [37]	Human motion detection
	Conventional GAN [38]	Generation of Brain Images
	GAN and deep transfer learning [39]	Detection of COVID-19 using chest imaging
	GAN with the deep neural network model [40]	Diagnose pneumonia caused by the coronavirus.
General	GE-GAN [41]	Estimation of traffic on the road
	3D-GAN [42]	High-quality texture Generation

3. Conclusions

GANs are a type of generative algorithm developed to tackle problems that need to be solved in a productive way, such as translating one image into another. With the fast-paced continuance of the AI research society and many ongoing publications pushing the technologies beyond their fundamental constraints, GANs are representing a new notion in deep learning. In this work, many GAN applications have been examined. Following a thorough review of Generative Adversarial Networks and their applications during the previous years, it is clear that there are numerous innovative and leading-edge learning models that fall into the categories of reinforcement learning, unsupervised and supervised models.

References

[1] P. a. M. J. Viola, "Rapid object detection using a boosted cascade of simple features.," in Proceedings of the 2001 IEEE computer society conference on computer vision and pattern recognition. CVPR 2001. Vol. 1. IEEE, 2001., 2001.

[2] A. T. N. M. a. N. V. Sahitya, "A Survey on Face Recognition Technology-Viola Jones Algorithm," International Journal of Computer Applications, 2016.

[3] A. Lanitis, "Evaluating the performance of face-aging algorithms," in 8th IEEE International Conference on Automatic Face & Gesture Recognition., 2008.

[4] C. M. C. J. S. a. S. J. G. Scandrett, "A person-specific, rigorous aging model of the human face," in Pattern Recognition Letters 27.15 (2006): 1776-1787., 2006.

[5] X. Z.-H. Z. a. K. S.-M. Geng, "Automatic age estimation based on facial aging patterns," in IEEE Transactions on pattern analysis and machine intelligence 29.12, 2007.

[6] A. C. J. T. a. T. F. C. Lanitis, "Toward automatic simulation of aging effects on face images," in EEE Transactions on pattern Analysis and machine Intelligence 24.4, 2002.

[7] W. C. Z. Y. Y. F. J. Y. S. S. X. &. S. N. Wang, "Recurrent face aging," in In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (pp. 2378-2386)., 2016.

[8] I. S. S. a. S. M. S. Kemelmacher-Shlizerman, "Illumination-aware age progression," in Proceedings of the IEEE conference on computer vision and pattern recognition, 2014.

[9] Chen, Hongyu, and Li Jiang. "Efficient GAN-based method for cyber-intrusion detection." arXiv preprint arXiv:1904.02426 (2019).

[10] Zhang, S., et al. (2020a). An Image Denoising Method Based on BM4D and GAN in 3D Shearlet Domain. Mathematical Problems in Engineering. 10.1155/2020/ 1730321.

[11] Van Sloun, R. J. G., Solomon, O., Bruce, M., Khaing, Z. Z., Eldar, Y. C., &Mischi, en M. (2019). Deep learning for super-resolution vascular ultrasound imaging. In Proceedings of the IEEE international conference on acoustics, speech and signal processing (ICASSP) (pp. 1055–1059). 10.1109/ICASSP.2019.8683813.

[12] Li.C., & Wand, en M. (2016). "Precomputed real-time texture synthesis with markovian generative adversarial networks", doi: 10.1007/978-3-319-46487-9_43

[13] Zhang H, Sindagi V, Patel V M. Image de-raining using a conditional generative adversarial network[J]. IEEE Transactionson Circuits andSystems for Video Technology, 2019

[14] Perarnau G, Van De Weijer J, Raducanu B, et al. Invertible conditional gans for image editing[J]. arXivpreprint arXiv:1611.06355, 2016.

[15] Liu, Ming-Yu, et al. "Generative adversarial networks for image and video synthesis: Algorithms and applications." Proceedings of the IEEE (2021).

[16] Jin, Y., Zhang, J., Li, M., Tian, Y., & Zhu, en H. (2020). Towards the high-quality anime characters generation with generative adversarial networks. ToegangVerkry. Nov 03

[17] Ye, G., Zhang, Z., Ding, L., Li, Y., & Zhu, en Y. (2020a). GAN-based focusing enhancement method for monochromatic synthetic aperture imaging. IEEE Sensors Journal

[18] Ma,.Q. et al., (2020). "Learning to Dress 3D people in generative clothing", doi: 10.1109/cvpr42600.2020.00650

[19] J ain, D. K., Zareapoor, M., Jain, R., Kathuria, A., &Bachhety, en S. (2020). GAN-Poser: An improvised bidirectional GAN model for human motion prediction. Neural Computing and Applications

[20] Shin, H.C. et al., (2018). "Medical image synthesis for data augmentation and anonymization using generative adversarial networks", doi: 10.1007/978-3-030-00536-8_1

[21] Islam, J., & Zhang, en Y. (2020). GAN-based synthetic brain PET image generation. Brain Informatics

[22] Zhang,.Y., Yin,.H., Huang,.Z., Du,.X., Yang,.G., & Lian, en D. (2018). "Discrete deep learning for fast content-aware recommendation"

[23] Zhaoa,.G. (2020)) "Bayesian conditional GAN for MRI brain Image synthesis | DeepAI"

[24] Mehdizadeh Aghdam,.S., Panahi,.A., & Krim, en H. (2019). "Sparse generative adversarial network", doi: 10.1109/ICCVW.2019.00369

[25] Cornick, M., Koechling, J., Stanley, B., & Zhang, en B. (2016). Localizing ground penetrating RADAR: A step toward robust autonomous ground vehicle localization. Journal of Field Robotics. 10.1002/rob.21605.

[26] de Oliveira, L., Paganini, M., & Nachman, en B. (2017). Learning particle physics by example: location-aware generative adversarial networks for physics synthesis. Computer and Software for Big Science. 10.1007/s41781-017-0004-6.

[27] Singh, M., Bajpai, U., Vijayarajan, V., & Prasath, en S. (2019). Generation of fashionable clothes using generative adversarial networks: A preliminary feasibility study. International Journal of Clothing Science and Technology. 10.1108/IJCST-12-2018-0148.

[28] Rodriguez Torrado, R., Khalifa, A., Cerny Green, M., Justesen, N., Risi, S., &Togelius, en J. (2020). Bootstrapping conditional GANs for video game level generation. In Proceedings of the IEEE Conference on Games (CoG) (pp. 41–48). Aubll. 10.1109/CoG47356.2020.9231576

[29] Mokhayeri,.F., Kamali,.K., & Granger, en E. (2020). "Cross-domain face synthesis using a controllable GAN", doi: 10.1109/WACV45572.2020.9093275

[30] Zhao, J., Xiong, L., Li, J., Xing, J., Yan, S., & Feng, en J. (2019). 3D-aided dual-agent GANs for unconstrained face recognition. IEEE Transactions on Pattern Analysis and Machine Intelligence.

10.1109/TPAMI.2018.2858819.

[31] Dutta, Indira & Ghosh, Bhaskar & Carlson, Albert & Totaro, Michael & Bayoumi, Magdy. (2020). Generative Adversarial Networks in Security: A Survey. 10.1109/UEMCON51285.2020.9298135.

[32] Chen, Hongyu, and Li Jiang. "Efficient GAN-based method for cyber-intrusion detection." arXiv preprintar Xiv: 1904.02426 (2019).

[33] Go, T., Lee, S., You, D., & Lee, en S. J. (2020). Deep learning-based hologram generation using a white light source. Scientific Reports. 10.1038/s41598-020-65716-4.

[34] Zhou, H., et al. (2020b). 3D high resolution generative deep-learning network for fluorescence microscopy imaging. Optics Letters. 10.1364/ol.387486.

[35] Tang,.H., Xu,.D., Yan,.Y., Torr, P.H.S., &Sebe, en N. (2020). "Local class-specific and global image-level generative adversarial networks for semantic-guided scene generation", doi: 10.1109/cvpr42600.2020.00789

[36] Yu, Y., Huang, Z., Li, F., Zhang, H., & Le, en X. (2020). Point Encoder GAN: A deep learning model for 3D point cloud inpainting. Neurocomputing. 10.1016/j.neucom.2019.12.032.

[37] Jain, D. K., Zareapoor, M., Jain, R., Kathuria, A., &Bachhety, en S. (2020). GAN-Poser: An improved bidirectional GAN model for human motion prediction. Neural Computing and Applications. 10.1007/s00521-020-04941-4.

[38] Islam, J., & Zhang, en Y. (2020). GAN-based synthetic brain PET image generation. Brain Informatics. 10.1186/s40708-020-00104-2.

[39] Loey, M., Smarandache, F., & Khalifa, en N. E. M. (2020). Within the lack of chest COVID19 X-ray dataset: A novel detection model based on GAN and deep transfer learning. Symmetry (Basel).. 10.3390/SYM12040651.

[40] Albahli, S. (2020). Efficient GAN-based chest radiographs (CXR) augmentation to diagnose coronavirus disease pneumonia. International Journal of Medical Sciences. 10.7150/ijms.46684.

[41] Xu, D., Wei, C., Peng, P., Xuan, Q., & Guo, en H. (2020). GE-GAN: A novel deep learning framework for road traffic state estimation. Transportation Research Part C: Emerging Technologies. 10.1016/j.trc.2020.102635.

[42] Spick,.R., Demediuk,.S., & Alfred Walker, en J. (2020). "Naive mesh-to-mesh coloured model generation using 3D GANs", doi: 10.1145/3373017.3373067.