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Review

Generative adversarial network: An overview of theory and applications

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A R T I C L E I N F O

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A B S T R A C T

In recent times, image segmentation has been involving everywhere including disease diagnosis to autonomous vehicle driving. In computer vision, this image segmentation is one of the vital works and it is relatively complicated than other vision undertakings as it needs low-level spatial data. Especially, Deep Learning has impacted the field of segmentation incredibly and gave us today different successful models. The deep learning associated Generated Adversarial Networks (GAN) has presenting remarkable outcomes on image segmentation. In this study, the authors have presented a systematic review analysis on recent publications of GAN models and their applications. Three libraries such as Embase (Scopus), WoS, and PubMed have been considered for searching the relevant papers available in this area. Search outcomes have identified 2084 documents, after two-phase screening 52 potential records are included for final review. The following applications of GAN have been emerged: 3D object generation, medicine, pandemics, image processing, face detection, texture transfer, and traffic controlling. Before 2016, research in this field was limited and thereafter its practical usage came into existence worldwide. The present study also envisions the challenges associated with GAN and paves the path for future research in this realm.

1. Introduction

A Generative Adversarial Network (GAN) emanates in the category of Machine Learning (ML) frameworks. These networks have acquired their inspiration from Ian Goodfellow and his colleagues based on noise contrastive estimation and used loss function used in present GAN (Grnarova et al., 2019). Actual working using GAN started in 2017 with human faces to adopt image enhancement that produces better illustration at high intensity. Adversarial networks were fundamentally inspired by the blog that has written by Olli Niemitalo in 2010 but the same idea is known as Conditional GAN.

In the examination of the GAN rigorous impact of 2D to 3D image conversation, initially, the corresponding dataset has to do live data fetching and create the benchmark with key features (Wu, Zhang, Xue, Freeman & Tenenbaum, 2016). Thereafter, for calculating threshold and suitability score, image merging has to be done. Image data pre-processing steps involve image segmentation and cleansing which follows the GAN training. Outcomes are expected pattern analysis and exactness of the image generation. Fig. 1 presents the example of a 3D generative adversarial network with five volumetric conventional neural layers of 2 strides and kernel sizes $4 \times 4 \times 4$.

Deep learning techniques could be used as generative models. Deep learning is an idea neural networks with many layers in one of the network architectures (Lecun, Bengio & Hinton, 2015). It can also be considered as a secondary field of ML algorithms inspired by the brain structure and functionality. In the applications of image identification, speech synthesis, text mining applications by receiving a distinct kind of data that hierarchical models can be built by representing probability distributions. Deep learning dependant on an end to end wireless communication system with conditional GANs using Deep Neural Networks (DNNs) do function of message passing like encoding, decoding, modulation, and demodulation. For this, the right judgement of immediate channel transfer state is required to transfer DNN (Ye, Liang, Li & Juang, 2020).

The most important feature of deep learning is discriminative models that can relate high dimensional sensory input sent to a class of labels. These generative models based on deep learning impact are lesser because approximation of obstinate probabilistic computation is difficult and leads to the utmost chances of judgement (He, Zhang, Ren & Sun, 2016; Lecun et al., 2015). If deep learning models are applied on genitive networks then the advantage will be that deep learning models are work on big datasets. These datasets are largely dependant on high-end machines and took a long time to do model training and less time for testing. Applications of GAN networks are exploring contemporary advancements and accomplishing our daily life needs.

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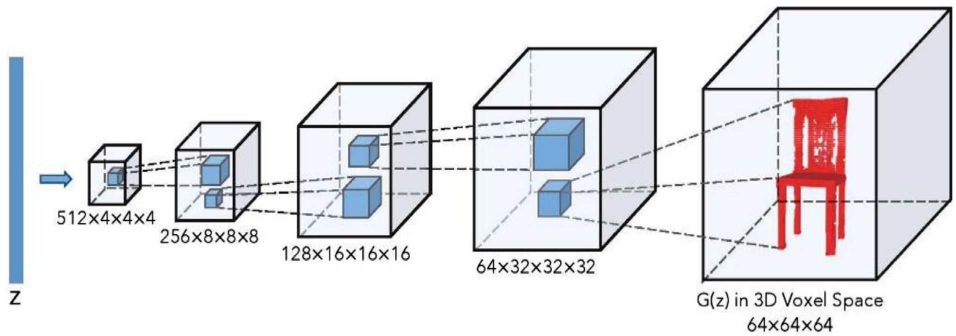

Fig. 1. Image generation /learning with the help of 3D GAN modelling (Wu et al., 2016).

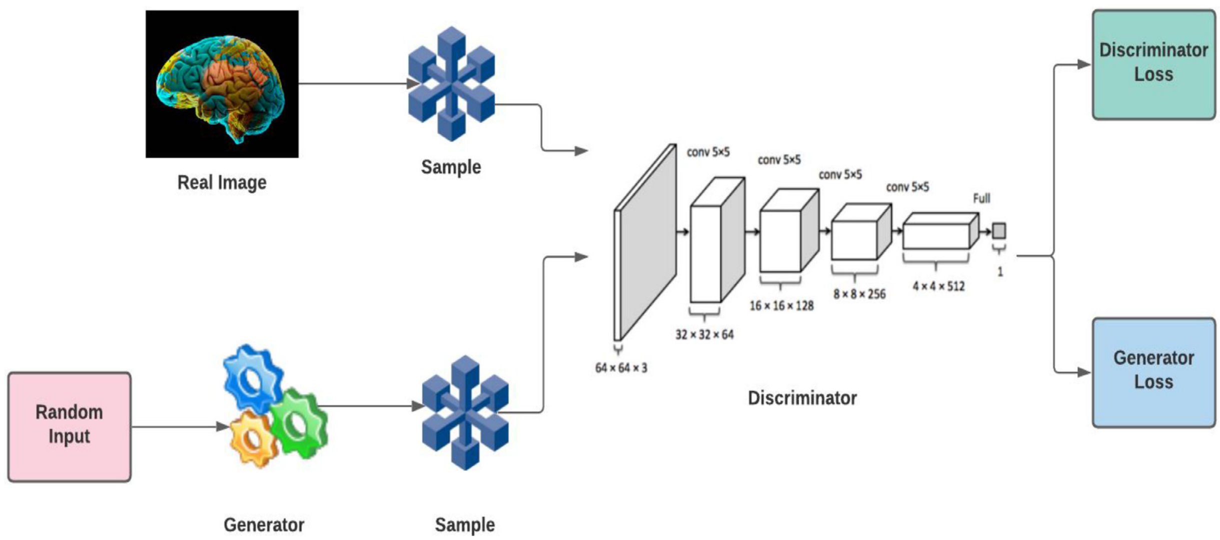

Fig. 2. Block diagram of the Generative Adversarial Network (GAN).

The GAN working based on three principles, firstly to make the generative model learn, and the data can be generated employing some probabilistic representation. Secondly, the training of a model is done can be done in any conflicting situation. Lastly by using the deep learning neural networks and using the artificial intelligence algorithms for training the complete system (Liu & Tuzel, 2016). The basic idea of GAN network deployment is for unsupervised ML techniques but also proved to be better solutions for semi-supervised and reinforcement learning. These factors all together enable GAN networks as comprehensive solutions in many fields such as healthcare, mechanics, banking, etc.

GAN is an analogous type of idea generated to model animal behaviour by researchers around 2013 (Bryant, 2013). It is a relative innovation in the field of deep learning that uses two different networks one that generates images. For instance, during fake image classification, one network called a generator creates fake images after an image by another network called a discriminator (Hsu, Zhuang & Lee, 2020). These networks are a category of deep learning models in particular convolutional neural network (CNN) frameworks. If at any time the discriminator is not able to notify the distinction between the two generate images and actual images representation is considered as converged. The training set trains to learn to produce novel information similar to the training set. Images generated from GAN are also the same images that give the impression of the seemingly genuine to the individual observer which may have real features (Marra, Gragnaniello, Cozzolino & Verdoliva, 2018). GAN can work on the unsupervised, supervised as well as for reinforcement. This generative network produces the image candidate and the discriminator used for evaluation. Fig. 2 is the block diagram representation of GAN.

The implementation of the 3D patterns of the image with GAN follows the initiation of the random generator and discriminator and the generator helps to understand the image type. The 2D image labelling has been trained by discriminator with a label as $y = 1$ and the 3D images produced in return labelled as $y = 0$. Thereafter, the discriminator checks the image weights by the discriminator and quantity them to the generator. This quantification network with images has been produced by label enforcement as $y = 1$, this process repeats till complete extraction of 3D image features.

As mentioned, the functionality of GAN is based on similar principles of neural networks as a training set has given as input to learning generate novel data that similar to the training set. Especially, the image data training by GAN can result in new images that are similar characteristics of human behaviour.

The step by step functionality of GAN has been explained as follows

- The users have produced using a generator by the discriminative network from the true data distribution.
- The system has trained so that the liability rate of the network can be increased and the discriminator network can be fooled by producing such candidates that are not synthesized i.e. still part of data distribution.
- A dataset acts as initial training data for the discriminator.
- For training samples datasets are presented till accuracy is achieved.
- The generator is trained to produce candidates when the discriminator is fooled when it is fed random input it processes them.
- Lastly, backpropagation has been applied to generators as well as discriminator where the former produces better images and the latter is skilled at fading artificial images.

- A deconvolutional neural network is a generative network and CNN acts as a discriminator.
- Sometimes GANs deal with mode collapse when the network fails to generalize in case missing entire modes from input data.
- Many solutions for one problem are proposed by the researchers.

In this work, the authors have presented a review analysis of the GAN functionality and its applications in real-time industries. Adversarial principle approaches with deep learning to produce generative models and simulation of other network theories have also been discussed. Besides, possible future developments in GAN models have also been explored.

The further sections of the presenting paper are as follows: Section 2, includes the methods conducting in the literature review and study selection process. In Section 3, the results of the review analysis including key findings have been discussed. In Section 4, the authors have presented the primary observations that evaluate the importance of GAN models, and finally, the conclusion section summarizes the findings and future works.

2. Methods

2.1. Search strategy

Authors have adopted the systematic literature review approaches that aligned with previous studies ((Agarwal, Chauhan, Kar & Goyal, 2017; Singh, Grover, Kar & Ilavarasan, 2020)). Three databases PubMed, EMBASE, and Web of Science (WoS) have been involved to extract the relevant works. Search strategies have been developed to identify the key literature amongst GAN applications and functionality. The possible synonyms, alternative words, and substitutes for the key terminologies and Boolean operators like "GAN models", OR "GAN applications" OR "GAN in image processing", OR "GAN AND cognitive computing' OR 'face detection' OR '3D classification with GAN' OR 'GAN in healthcare' AND 'deep learning transformation with GAN' have been included.

The authors worked the primer appraisal freely by perusing the abstracts and drafting a rundown of the articles that they thought about qualified. At that point, the previously mentioned search words were looked at for disparities, and when one was distinguishing from others of a similar kind, the various thoughts were talked about before reaching the final selection. When the authors chose which articles were qualified to be remembered for the survey, they read all the articles to assemble information helpful with the end goal of the exploration exertion (Grover, Kar & Vigneswara Ilavarasan, 2018). The data assessment was directed freely and all opinions were compared to define an agreement.

The review analysis of research articles included in the previous five years (2016–2020) and in all applications where GAN has been involved. The following applications have emerged: 3D object generation, medicine, pandemics, image processing, face detection, texture transfer, and traffic controlling. Prior Studies are considered to be less relevant as their practical applications increasingly starting from 2016.

2.2. Selection criteria

The GAN literature search outcome provided 2084 records that are categorised by publications associated with the objective of this study. In particular, 1141 records in Scopus (Embase), 537 in WoS, and 406 in PubMed were found. The yearly availability and library search distribution has presented in Fig. 3.

The following three types of articles have been considered: Original papers, reviews, and analytical studies. The inclusion criteria involved during the selection process a) study type: original research, preliminary analysis, literature works published after only 2016; b) articles with a major focus on GAN applications and the latest advancements of GAN models. More specifically, the records were screened for the three criteria in the following sequence before the inclusion of final analysis:

1) Does the selected paper present the application-based review GAN works?
2) Does the publication is discussing GAN progress in real-time industries?
3) Does the paper accurately address the research question and objectives?

The exclusion criteria were a) records of different characteristics managed with inclusion criteria, b) language, and c) studies with no precise GAN objectives. The objective here is to understand how these models are evaluated, which industries are connected to GAN so that sophisticated applications can be spoken for the beneficiary of society.

3. Results

In this section, the authors have presented the stages involved in the literature search and the evolution of GAN models in different applications. Broad areas of GAN applications are increasing quickly with time and its functionality including some of the major applications in each thematic view has been discussed below.

3.1. Preliminary records outcome

Following the initial screening of the abstracts, 1783 articles that were not appropriate to the goals of this investigation were wiped out for the accompanying reasons: 1757 articles were identified as duplicates, and 26 articles are not in English. In the second phase of screening, the remaining 301 papers distributed equally to authors for independent evaluation, and among only 61 articles are successfully satisfy the above-mentioned research objectives. Of these, following the perusing of the full-text form, nine were rejected because they did not examine the relationship between GAN modelling and image diagnosis which didn't fall inside the recently indicated consideration standards. Ultimately, 52 papers are considered for further analysis. The literature process model consists of screening steps that are further has presented in Fig. 4.

3.2. Survey on GAN applications

This section presents the explanation of the involvement of generative adversarial networks in major domains and Table 1 presents the overview of GAN studies involved in different domains.

3.2.1. GAN in 3D object generation

Investigating powerful 3D image generation techniques is a basic viewpoint in the area of computer vision and computer graphics. To identify 3D objects and enhance computer vision, some studies were employed GAN networks. For instance, Yu et al. proposed a network that processes unclear data with no labelling, and the idea of 3D point encoder cloud GAN Point encoder has been used in painting and uses max-pooling layer to resolve points for the learning process. Two networks are worked as input encoder and decoder pipelines which results in a better characteristic representation of the input point cloud (Yu, Huang, Li, Zhang & Le, 2020).

An architecture based on 3D-CNN lightweight multi-level architecture connected super-resolution network and if generative adversarial network-based training is provided to the network it creates sharp images with better quality (Chen et al., 2018). A GAN focusing enhancement of 2D monochromatic images in the creation of realistic 3D imaging (Ye, Zhang, Ding, Li & Zhu, 2020). A generative 3D model which is a group of people wearing clothes and doing 3D scans with different pose and outfits and is trained with a conditional Mesh-VAE-GAN so that deformation of clothing can be learned from the SMPL body model so that analysis of human motions and poses can be taken (Ma et al., 2020). Generalization for complex dressed people in common images and videos is not done but learned by minimizing clothes 3D scans. A

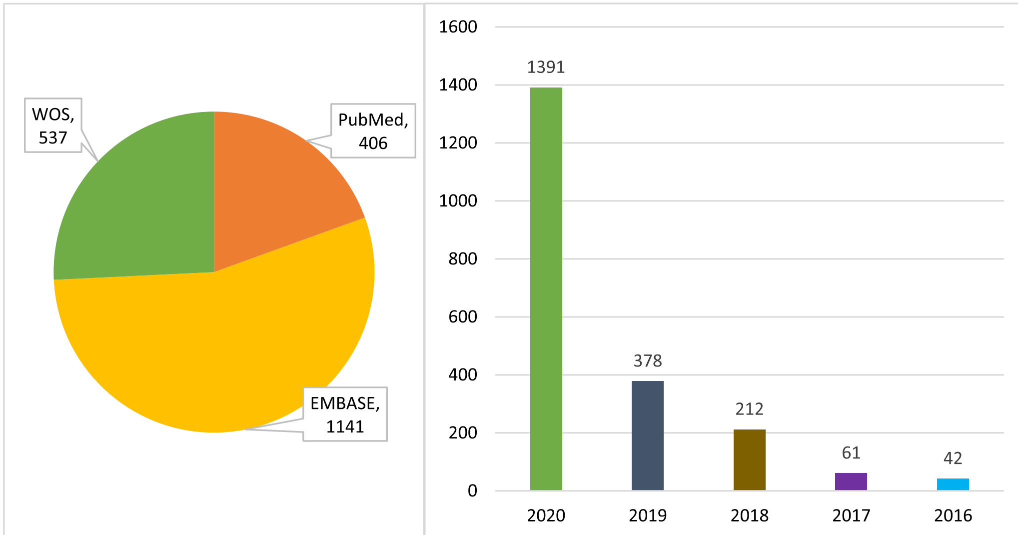

Fig. 3. Library Search outcomes: Library distribution (left) and Yearly distribution (right).

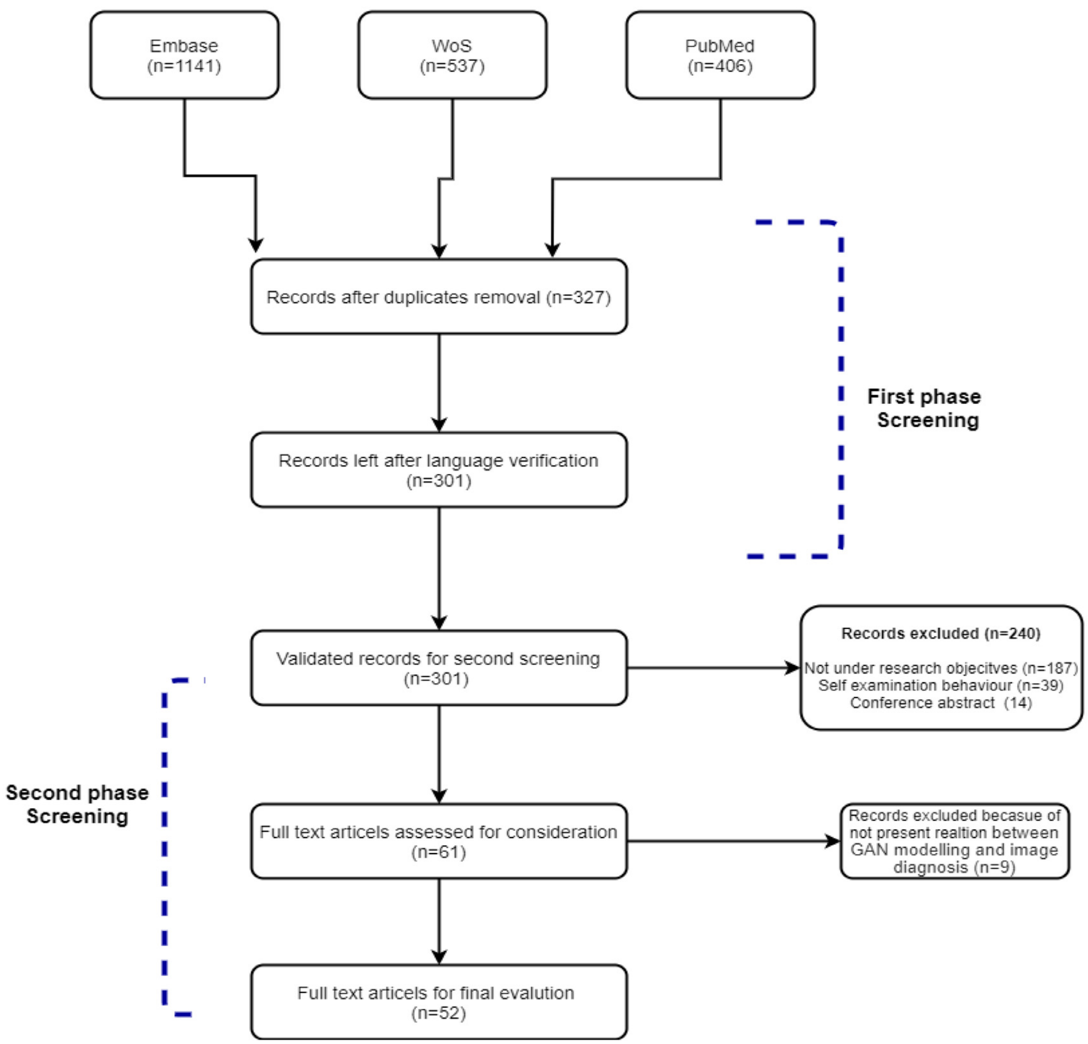

Fig. 4. Steps involved in records screening.

Table 1
Key studies that define different GAN applications.

Type	Authors [Ref]	Year	Model	Application
3 D object generation	Yu Y.et al. (Yu et al., 2020)	2020	GAN Point encoder	Processes unstructured data with no labelling
	Y Chen et al. (Chen et al., 2018)	2018	3D-CNN	Create sharp images of good quality
	G Ye et al. (Ye et al., 2020)	2020	Deep learning-based GAN	Improving 2D monochromatic images
	Q Ma et al. (Ma et al., 2020)	2020	Generative 3D model	Human motion capturing
	Y Jin et al. (Jin et al., 2020)	2020	GAN model with three-tier adversarial principle	Production of high-quality 3D objects
Medicine	S Baek et al. (Baek et al., 2020)	2020	GAN and Mesh Model	Production of MR Images in sealed pixels
	Jain D K et al. (Jain et al., 2020)	2020	GAN poser	Detection of human motion
	A Teramoto et al. (Teramoto et al., 2020)	2020	Deep convolutional neural network (DCCN) with GAN	Classify cytological images
	M D Cirillo et al. (Cirillo et al., 2020)	2020	Vox2Vox: 3D-GAN	Brain tumour segmentation
	H C Shin et al. (Shin et al., 2018)	2018	Conventional GAN	Identify medical images
	J. Islam et al. (Islam & Zhang, 2020)	2020	Conventional GAN	Brain image generation
	H Lan et al. (Lan & Toga, 2020)	2020	SC-GAN	NeuroImage synthesis
	G Zhaoa (Zhaoa, 2020)	2020	Bayesian Conditional GAN	MRI Brain Image Synthesis
	R Oulbacha et al. (Oulbacha & Kadoury, 2020)	2020	Pseudo-3D Cycle GAN	MRI to CT Synthesis of the Lumbar Spine
	X Zhang et al. (X. Zhang et al., 2020)	2020	Deform-GAN	Noise reduction in 3D medical images
	D Yang et al. (Yang et al., 2019)	2019	Adversarial image-to-image networks	Medical image synthesis and semantic segmentation
Pandemics	Loey M et al. (Loey et al., 2020)	2020	GAN and deep transfer learning	COVID-19 detection with chest images
	S Albahli (Albahli, 2020)	2020	GAN with the deep neural network model	Diagnose coronavirus disease pneumonia
Image processing	C Li et al. (Li & Wand, 2016)	2016	Markovian GAN	Generate 3D image from 2D image
	H Zhou et al. (Zhou et al., 2020)	2020	Dual GAN	Recovering of high-resolution images
	T Go et al. (Go et al., 2020)	2020	Deep neural network-based GAN	Perform image transformation
	S Zhang et al. (S. Zhang et al., 2020)	2020	Conventional GAN	Image denoising
	H Tang et al. (Tang et al., 2020)	2020	Conventional GAN	Semantic guided scene generation
Face detection	F Mokhayeri et al. (Mokhayeri et al., 2020)	2020	A new Controllable GAN (C-GAN	Cross-domain face synthesis
	J Zhao et al. (Zhao et al., 2019)	2019	Dual-Agent Generative Adversarial Network (DA-GAN)	Unconstrained Face Recognition
	M Kowalski et al. (Kowalski et al., 2020)	2020	Deep learning-based GAN	Face Image Generation
	D P Jaiswal et al. (Jaiswal et al., 2020)	2020	Conventional GAN	Face animation
Text transferring	L Sixt et al. (Sixt et al., 2019)	2019	Conventional GAN	Generating realistic labelled data
	R Spick et al. (Spick et al., 2020)	2020	3D-GAN	Generate high-quality texture by adding colour
Traffic control	D Xu et al. (Xu et al., 2020)	2020	GE-GAN	Road traffic estimation
	Fathi-Kazerooni S et al. (Beery et al., 2020)	2020	GAN Tunnel	Detection of traffic images

3D GAN developed for the creation of 3D objects probabilistic space in volume convolutional networks and generative adversarial networks. The model uses a three-tier adversarial principle in place of heuristic enable the generator to detain object structure absolutely and produce high-quality 3D objects along with generator maps from a small dimensional to 3D objects (Jin, Zhang, Li, Tian & Zhu, 2020).

3.2.2. *GAN in medicine*

Machine learning and deep learning concepts are highly involving in the medical domain especially to identify chronic diseases (Battineni, Sagaro, Chinatalapudi & Amenta, 2020), (Kaur et al., 2018). It is reported that GAN can produce the MR Images successfully in sealed pixels (Baek, Kim & Kim, 2020). Jain et al. proposed a novel technique based on a generator discriminator called GAN-Poser for the prediction of human motion with 3D input of human skeleton image (Jain, Zareapoor, Jain, Kathuria & Bachhety, 2020). A bidirectional GAN framework iterative prediction scheme so that form crumple can be predicted to normalize the training rather than using traditional Euclidean loss. The model gives better performance over conventional deep learning methods evaluated on the datasets called NTU-RGB-D and Human3.6 M. Besides, tumour classification by MR images also possible by applying the deep learning associated GAN's models, and it results in a comprehensive classification of glioblastoma patients (Teramoto et al., 2020).

Brain tumour images showing that 3D volume using GAN for segmentation called Vox2Vox works on multi-channel 3D MR images and the best output can be achieved when generator loss is weighted 5 times compared to the discriminator loss (Cirillo, Abramian & Eklund, 2020). A clinical application by adopting GAN that helps in the unsupervised image to image conversation and identification of medical images (Shin et al., 2018). It is also proven that artificial medical metaphors these networks classify brain PET images for the identification of three-stage (i.e., normal, mild, severe) Alzheimer's disease (AD) (Islam & Zhang, 2020). It is stated that any system is designed on 3D conditional GAN and uses a normalization of spectral stabilizes criteria of feature matching for achieving convergence optimization. An autonomous conditional GAN considerably surpasses traditional 2D conditional GAN and 3D functioning so that a dynamic 3D deep learning-based neuroimaging synthesis can be done (Lan & Toga, 2020).

An enhanced deep Super-Resolution Generative Adversarial Network which creates images for three diverse stages of brain normal control, mild cognitive impairment, and disease are image stages of Alzheimer's (Islam & Zhang, 2020). Likewise, a Bayesian conditional GAN with unnecessary feature dropouts to get better image mixture exactness. Uncertainty in feature interpretation has been generated by the Bayesian network done on the samples of brain tumour datasets of more than 100 examples when compared to traditional Bayesian neural networks (Zhaoa, 2020).

An unsupervised approach Pseudo-3D Cycle GAN architecture in which neighbouring parts in mixture along with cyclic loss function ensuring consistency from the fusion of CT images of the lumbar spine for guided surgical images from T2 weighted MRI acquired for diagnostics.

This approach makes use of a trainable pre-processing pipeline using low capacity fully convolutional networks to normalize MRI data to cascade for the segmentation of vertebral bodies and pedicles (Oulbacha & Kadoury, 2020).

The alignment of the sequences and modalities when there is a registration of the 3D medical images by use of unsupervised learning and gradient descent. This approach provides a decrement in the noise and blurriness in 3D medical images by the GAN model (Zhang, Jian, Chen & Yang, 2020). Yang et al. (2020) adopted a method of deep learning network has created as a baseline for medical image segmentation using GAN with machine learning, computer vision, and medical image analysis. It is also able to get a better segmentation presentation with global shape constraints and applied to domain adaptation for both image synthesis and semantic segmentation (Yang, Xiong, Xu & Kevin Zhou, 2019). Medical images and ML and deep learning create a cochlea signed distance map depending on four input parameters that leads to a 60-fold improvement in the time of computation compared to more classical SDM generation methods. The complexity of SDM for 3D parametric shapes is overcome by SDM generation neural network is implemented with dimensional cochlea shape model parameterized by 4 shape parameters (Zhang et al., 2018).

3.2.3. Pandemics

In the pandemics like novel coronavirus (COVD-19) (Chawla, Mittal, Chawla & Goyal, 2020), deep learning models are highly involved to mitigate the virus severity in the form of bots (Battineni, Chintalapudi & Amenta, 2020). These models coupled to GAN can be used to identify the infection severity. The studies like Loey et al. have proved that GAN couple with deep learning models is the best approach for COVID-19 detection by involving chest X-ray images. The authors collected set 307 chest X-ray images and identify high accuracy images that are helping to detect novel coronavirus (Loey, Smarandache & Khalifa, 2020). It is reported that a model called COVID-GAN that is associated with synthetic chest X-ray images has successfully done image classification with a combination of shaping the synthetic images and achieved 89% accuracy (Albahli, 2020).

3.2.4. Image processing by GAN

GAN models can solve the ultrasound image resolution by integrating deep learning models. These are employed to end encoding and decoding for making high-resolution images from regularly capture prostate ultrasound images (Van Sloun et al., 2019). GAN can produce different lesion classes from a small sample size of each lesion, and after application of deep convolutional GAN to generate a 3D image from 2D image resulting in faster analysis of images (Li & Wand, 2016). For that optical clearing of images had been involved for the high-resolution image volumes that match low-resolution volume images (Zhou et al., 2020).

Holography defines the creation of a unique photography image with no involvement of lens. Some studies applied GAN identification of holograms. Digital holography microscopic which records hologram contains 3D data using neural network and GAN had applied (Go, Lee, You & Lee, 2020). Image to image conversion is not only focused on a simple white light source to holographic picture by measuring the network comparison of generated and true holograms of microspheres in a 3D image.

A process of achieving clean images from a hard threshold with wiener filtering for solving stained images. These images are disintegrating to get coefficients of a 3D block-matching algorithm to get clean images by training latent clean images through GAN. For that peak signal-to-noise ratio, structural resemblance, and edge preserve index are taken as criteria for noise removal in visual effects (Zhang et al., 2020). Besides, Tang et al. addressed that the image generation of small objects and images of local texture based on the guided scene is quite difficult. For that, a scene is generated with local background and a local class with semantic maps has been designed for the guidance which separately constructs and learns sub generators concentrating on the generation of different screens (Tang, Xu, Yan, Torr & Sebe, 2020).

3.2.5. Face detection applications by GAN

Fake face identification is crucial for intelligent frameworks since generative models becoming famous by day-to-day. Because of enhancement in quality in the fake face, the prepared models become increasingly not efficient to identify the fake faces and corresponding training data has been mentioned as outdated. In such cases, if the performance of faces has to be recognized in the video surveillance system, and can be improved by imitating face generation. Therefore, scholars proposed a cross-area face imitation combined with the GAN named as controlled GAN (CGAN) (Mokhayeri, Kamali & Granger, 2020). In CGAN refinement, model simulation has been conducted by the face images for noise removal.

A Dual-Attention Generative Adversarial Network (DA-GAN) in which a photo-realistic face frontal by capturing both contextual dependency and local consistency during GAN training for highlighting the required pose and illumination discrepancy in the image (Zhao et al., 2019). Also, Kowalski et al. proposed a model called CONFIG-Net which is an attribute detection network. The neural face model permits the dominant person image trained on the real face and fake face detection by synthetic data, and it is a separating aspect such as pose, facial expression, hairstyle, etc. (Kowalski et al., 2020). The automatic generation of facial images using GAN in solving the problem of facial images of animated works (Jaiswal, Kumar & Badr, 2020).

3.2.6. Texture transferring

A GAN based texture interpretation in the need of computations, by that high-resolution texture sampling and shading in million times fold can be performed. Recently, deep learning has been used by researchers on content combinations and style representations from a different type of image analysis. The content and style extraction has called texture transferring. In Sixt, Wild and Landgraf (2019), the authors trained GAN with 3D extracted image with no texturing results. The output image is another 3D rendered image with texture. Finally, the generative deep learning model produces an output image trying to match the target image. Given this, Spick et al. proposed a model initial voxel-based 3D GAN learning model that includes colour to produce generated samples by adapting channels of voxel inputs. If unsupervised learning is used to generate high-quality texture then there is an improvement in turnaround time and these are tested on a thin collection of inputs from a set of open access textured models (Spick, Demediuk & Alfred Walker, 2020).

3.2.7. Traffic control

Different investigations are been highlighted that precise road traffic details by detectors are more accurate than different model predictions. Xu et al. developed a traffic road estimation framework using deep learning called GE-GAN where dual street systems of two cities are been used as a case study. This is done by using the data from neighbouring links to guess the road traffic of the states by application of graphs for the illustration of the road network and using GAN's (Xu, Wei, Peng, Xuan & Guo, 2020). The traffic images can detect and classify the traffic occurrences, this helps to control self-driving cars on roads (Fathi-Kazerooni & Rojas-Cessa, 2020).

4. Discussion

In this study, the authors have presented GAN architecture and functionality along with its major domain applications. A survey of image segmentation by deep learning approaches like GAN can produce rigorous literature review and studying the range of works on segmentation of semantic and illustration level, networks covering recurrent networks, encoder-decoder architectures, convolutional pixel labelling networks, and visual attention generative with adversarial settings. The advantages, challenges, strengths, similarity of other models, their datasets, and prospects in the above area can be well explained (Sultana, Sufian & Dutta, 2020). Because of recent advancements in deep learning and the presentation of huge 3D CAD datasets like Shape Net (Chang et al., 2020), there have been some motivating works in deep learning object notation. Unique about part-based techniques, a large number of these generative methodologies don't expressly show the idea of parts or recover them from an object repository; as an alternative, they arrange fresh objects based on learned object presentation.

A pro-signed distance map approach generates a cochlea signed distance map depending on four input parameters and demonstrated with help of deep learning resulted in sixty times enhancement as compared to traditional generation methods (Wang et al., 2020). This is a difficult issue because compared with the space of 2D images, it is harder to show the space of 3D shapes due to its higher dimensionality. Their present outcomes are empowering, however frequently there still exist gaps in the created objects. To overcome those, generative adversarial networks have been introduced in this study. The common datasets for generation of 3D objects using GAN are 2D-to-3D deformable sketches (Zorah Lähner, Rodolà, Schmidt & Bronstein, 2020), 3D deformable objects in clutter (Cosmo, Rodola, Masci, Torsello & Bronstein, 2016), ANN_SIFT1M (sift 1 M dataset & ANN - Frankie Yan's Blog, 2020), CIFAR-10 (CIFAR-10 & CIFAR-100 datasets, 2020), and CLEF-IP 2011 evaluation on patent images. The data created by GANs are casual vectors under the category of concentrated casual vectors and behave as Gaussian mixtures by using deep learning algorithms (El, Seddik, Louart, Tamaazousti & Couillet, 2020).

The library-like Py-Torch is the most famous GANs packages that can implement and provide a comprehensive approach of GAN training with different image datasets. This package helps to control the issues during GAN model implementation using different frameworks and at the same time evaluating when the same metric has been used (Lee & Town, 2020). A deep learning fault detection process based on unbalanced data with global optimization GAN leads to high misclassification. Such a method of novel generator and discriminator are planned to using an auto encode reaching to global optimization and refine unqualified produced samples from qualified samples for error analysis (Zhou, Yang, Fujita, Chen & Wen, 2020).

In other applications like space sciences, the GAN network to build better astronomical images to predict as well as simulate gravitational sensing for dark matter research to model distribution in any direction in space (Mahdizadehaghdam, Panahi & Krim, 2019). Scholars mentioned that radar-based map deals with the difficulty of signal loss and a map has been created to interpret the climatic changes and lighting compatible with sensor nature, and the promise of vehicle localization has done when a picture from FMCW radar is placed on a land vehicle (Cornick, Koechling, Stanley & Zhang, 2016). Besides, GANs projected a better method of modelling high energy jet formation, approximate hurdles in costly simulations of particle physics experiments ((de Oliveira, Paganini & Nachman, 2017; Lin, Bhimji & Nachman, 2019)). To classify the images using GAN the discriminator is changed to predict the label of the class of any image despite accepting as input. To stabilize the training and generation of large excellence images can be allowed. In arts like fashion, Fs-GANs have been implemented for imaginary pictures of the models without hiring a photographer hiring, makeup artists, also cut down the studio costs (Singh, Bajpai, Vijayarajan & Prasath, 2019). Fashion advertising companies using GANs having various groups of models increasing people who resemble models. Landscapes, portraits, album covers can be created using GAN.

GAN networks can also be used to creating games by a technique of scaling the 2D texture resolution of video games and recreating in larger resolutions (Rodriguez Torrado et al., 2020). Process of training and after that down sampled so that it can be fitted in-game native resolution. The final outputs are similar to the super sampling method of anti-aliasing. If such networks are trained properly can provide a clear as well as a sharper image with high magnitudes improves quality if compared with the original. The images were developed to retain the original level of details and colours. The other wide range of GAN applications including Speech to image construction, visualize climate changes, face ageing, photo blending, motion video capturing, video prediction, etc.

4.1. GAN limitations

However, GAN architecture has some limitations. The images created by GAN look misleadingly like a photograph of a real person based on the analysis of portraits. Different concern by the people has been raised for using the human image synthesis by GAN potentially by frauds thereby producing the fake and photographs and videos without permission. On social media, fake profiles can be prevented using GANs for generating the unique or pragmatic pictures of persons that do not exist. DARPA's Media Forensics programs help in countering such fake media profiles produced using GANs and along with that many laws are passed and they are implemented by the year 2020.

4.2. Future works

GANs are representing a new concept in deep learning with the fast pace continuation of the AI research society and bringing about many ongoing publications pushing the technologies beyond its primary limits. The deficiency of the GAN essential hypothesis is an obstruction for GAN models to develop high-quality generative models. Accordingly, the most significant implementation for future works is to have breakthroughs in hypothetical aspects to tackle issues, for example, difficulties in training, non-union, and model breakdown (Salimans et al., 2016). Despite some generally improved strategies, for example, weights pruning and regularization (Arjovsky, Chintala & Bottou, 2017; Gulrajani, Ahmed, Arjovsky, Dumoulin & Courville, 2017), Nash Equilibrium (Kodali, Abernethy, Hays & Kira, 2017), and new loss functions (Mao et al., 2017), future improvements are still in need. Besides, GAN can address the new theories and research outcomes in ML models, for example, attention mechanisms can be incorporated for capturing global features. GAN research with policy gradient procedures in reinforcement learning can overcome the weakness in dealing with discrete variables, therefore GAN can work in different conditions to increase the scope of its application (Kurakin, Goodfellow & Bengio, 2019).

5. Conclusions

GANs established in a way to the comprehensive domain of independent data expansion and solve problems that require a generative solution like the image to image transformation. In this work, many applications of GAN have been analysed and after going through in-depth revision of GAN and deep learning and its applications in preceding years it can be seen as there are many cutting edge learning models lay the category of supervised, unsupervised, and reinforcement learning. Furthermore, many deep learning datasets and frameworks are used to present the performance of deep learning problems.

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Authors' contributions

A.A. selected the studies, performed a literature review, and participated in drafting the manuscript. M.M. guided the study's overall stages, revisited the manuscript critically for important intellectual content, and approved the study. G.B. designed the study, selected the studies, performed literature review, methods, data extraction, analysed data, interpreted the result, and drafted the manuscript. All authors approved the final article.

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