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REVIEW ARTICLE

A Systematic Review on Generative Adversarial Network (GAN): Challenges and Future Directions

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Abstract
Generative adversarial network, in short GAN, is a new convolution neural network (CNN) based framework with the great potential to determine high dimensional data from its feedback. It is a generative model built using two CNN blocks named generator and discriminator. GAN is a recent and trending innovation in CNN with evident progress in applications like computer vision, cyber security, medical and many more. This paper presents a complete overview of GAN with its structure, variants, application and current existing work. Our primary focus is to review the growth of GAN in the computer vision domain, specifically on image enhancement techniques. In this paper, the review is carried out in a funnel approach, starting with a broad view of GAN in all domains and then narrowing down to GAN in computer vision and, finally, GAN in image enhancement. Since GAN has cleverly acquired its position in various disciplines, we are showing a comparative analysis of GAN v/s ML v/s MATLAB computer vision methods concerning image enhancement techniques in existing work. The primary objective of the paper is to showcase the systematic literature survey and execute a comparative analysis of GAN with various existing research works in different domains and understand how GAN is a better approach compared to existing models using PRISMA guidelines. In this paper, we have also studied the current GAN model for image enhancement techniques and compared it with other methods concerning PSNR and SSIM.

1 Introduction

Generative adversarial networks are the sub-class of the generative model, with the competence to produce/verify a new set of data. A generative adversarial network was introduced in 2014 by researchers Ian J GoodFellow et al. [28] in his research paper published in IEEE Journal.

Most neural networks aim to learn from the limited data set, which usually faces misclassification and overfitting problems. The GAN model is a powerful architecture with a component of self-generate, self-learning and competence to overcome the limitation of traditional networks.

According to GoodFellow et al. [28] research paper published in 2014, GAN and its structure are described as a two-player min–max game or Nash Equilibrium with the function value V(D,G). The detailed mathematical description is given by Good Fellow is shown in Formula 1.

$$\min_G \max_D V(D, G)$$
$$V(D, G) = E_{x\ pdata(x)}[\log D(x)] + E_{z\ p(z)}[\log(1 - D(G(z)))] \quad (1)$$

In 2015, a new variant of GAN was proposed by ABC, and this work has become a basic approach for all upcoming variants of GAN. In this work, the GAN is mainly broken down into two modules, Generator G(A) and Discriminator D(A). Here, the generator generates the data, similar to the training dataset, and the discriminator is a network trying to identify the real and generated data. The GAN model

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work on the principles of game probability. The theory is to generate a random variable (A) whose properties are similar to the actual variable. Specifically, the generation of the random variable experiment is repeated N number of times until it gets the actual variable value which is known as Probability(P). And the possible outcome of this is known as sample space represented by Ω. Overall we claim it as probability distribution function P(A) where the probability of all outcomes can generate the result R as shown in Formula 2.

$$P: \Omega \rightarrow Z$$

$$(\textit{assuming the probability of generated random variable is always positive } P(A) \geqslant 0)$$

Hence, we can say the summation of all probability can give an actual variable, i.e. ΣAЄΩP(A) = 1. A simple real-time example of GAN is two people playing Guess the number in the mind game. R. Chang et al. 2023 [143] and Z Pan et al. 2019 [105] are some of the experimental works that supported the above hypothesis. The simple GAN model concerning Game probability is shown in Fig. 1.

1.1 Basic Modules of GAN

GAN deep learning module is mainly made of two adversarial network modules Generator and a Discriminator.

Generator: It is an unsupervised model in GAN that generates new values in input distribution based on the summary of real input variable distribution. The generator reads fixed-length random vectors based on the Gaussian distribution concept; after training, the generator forms compressed data distribution corresponding to multi-dimensional vector space. The architecture of the generator is shown in Fig. 2.

Discriminator: Discriminator is a supervised GAN model that uses input and general variables based on the class label. The discriminator inputs value from real and generated dataset and predict a binary label 0 and 1, classifying the received data as fake or the same, respectively. The architecture of the discriminator is shown in Fig. 3.

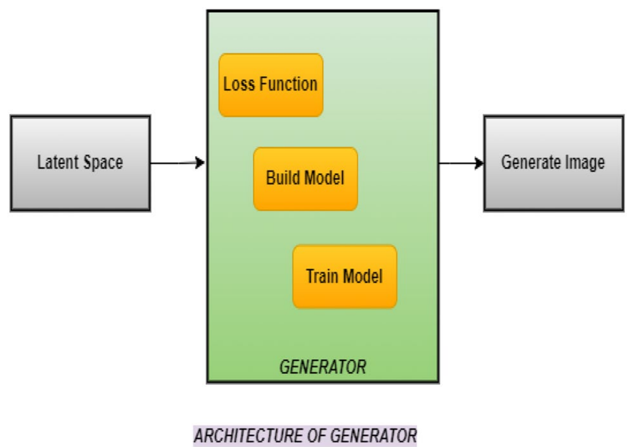
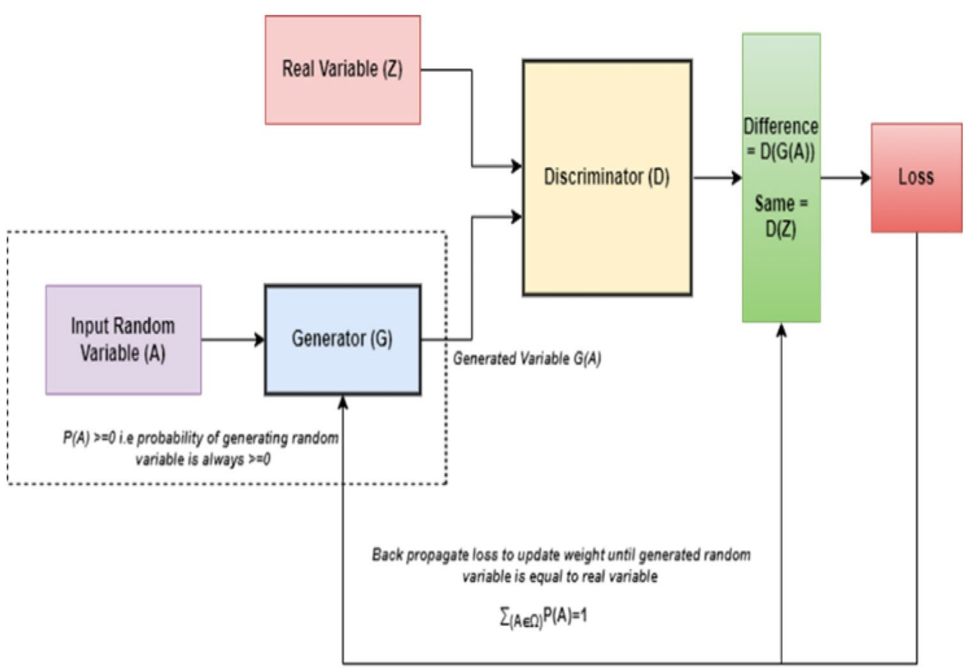


Fig. 2 Architecture of Generator in GAN

Fig. 1 Architecture of GAN



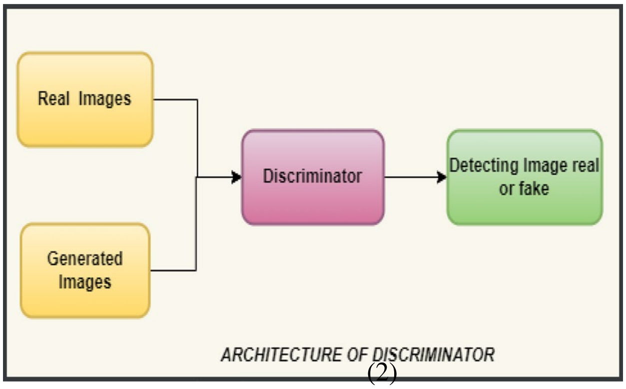


Fig. 3 Architecture of Discriminator in GAN

1.2 Applications of GAN

A generative adversarial network is a trending neural network model with several fascinating applications in various domains. The usage of the GAN model in many applications has shown a drastic change in the result and system accuracy. In this study, we have discussed some of the well-known applications of GAN as follows.

1.2.1 Application of GAN in Cyber and Network Security

The various anomalies in the security system are damaging the system and our privacy. The new GAN approach is vital in improving cyber security and building a safer system environment that protects against various attacks. GAN is one of the latest ideas in self-driving cars to enhance their safety and protection during navigation and collection of specific sensor data. These days, applying GAN in cyber security has become one of the exciting fields among researchers. A large set of research works can be observed using the GAN approach in the cyber security area.

The GAN model can be practiced to detect various cyber intrusions like distributed denial of service attacks, botnet attacks etc. [1]. To detect cyber-physical system attacks, FID-GAN, an unsupervised intrusion detection system, is designed [2]. Many imbalanced data set problems during intrusion detection are solved by using simple GAN and GAN with Earth-Mover distance in [6, 7]. To enhance the accuracy of GAN model, the labelled sample set is expanded by using an advanced binary classification model [3]. In Yixuan Wimu et al., a mining approach is presented based on the fuzzy rough set, CNN and GAN to enhance intrusion detection based on feature extraction [4, 5]. GAN and modified versions of GAN, like PAC-GAN, have notably contributed to detecting malware and standard packets in cyber security [8, 9].

Overall, GAN can be used in most of the studies related to threat detection [10–12], false data injection attacks imbalanced data problems etc., in the cyber and network security domain.

1.2.2 Application of GAN in Healthcare Industry

GAN is one of the fascinating inventions of AI that has contributed to most of the domains in today's research environment. Most of the SURPRISING and splendid tasks of human and AI bots are the work of GAN. The healthcare industry is one of the majorly benefited fields of GAN. Radiology images like CT, MRI, ultrasound, radiography, and elastography resolution can be enhanced by GAN. The small data set problem during the training phase is one of the major issues addressed in the healthcare domain by GAN.

To understand the role of GAN in healthcare, we have gone through different research works. The major work was observed in enhancing image clarity. In Yuhui Ma et al., [13] a versatile novel approach, Still-GAN, is introduced to enhance low and high-quality images. Lesion Focused Multiscale in [14] and enhancement of low-resolution counterparts of CT images by the GAN-Circle approach [15] are a few other enhancement techniques noted. To enhance and generate a high-resolution 3D medical image, hierarchical amortized GAN is used in research work presented in [16].

The other notable application of GAN is image generation and synthesis. Chikato Yamasoba et al. [17] presented an approach to generate different modality images using DCGAN and Cycle GAN. In [18], a one more approach where DC-GAN is used for medical data synthesis, and generating MR images using GAN is observed [19]. Strategies like GAN augmentation for liver lesion classification [20], fund-GAN approach to augment fundus image for retinal image classification [21], pseudo-3D cycle GAN lumbar spine data synthesis [22] and 3D multi-conditional GAN for image augmentation in lung module classification some more work reviewed in image augmentation [23]. Finally, we noticed a few more applications like medical image segmentation by using MS-GAN [24], U-net Based GAN [26], image fusion on GAN [25] and tumour classification [27]. In conclusion, GAN has become a boon and advantage for the growth of the medical field.

1.2.3 Application of GAN in Computer Vision

In this survey, we have considered some of the applications of GAN, which have made revolutionary improvements in computer vision. The application of GAN in computer vision can be classified into the generation of image datasets, super-resolution, creating human face photographs, image-to-image translation, generating realistic pictures, face frontal view generation and generating new human poses.

Generating image datasets is an approach to creating new plausible images from existing images. Firstly, this approach was designed by Ian Goodfellow et al. in 2014 [28]. In this paper, the author has generated a likely image from the MINIST data set. The MINIST dataset combines CIFAR-10 small objects and the Toronto face database. In 2015 [29], Alec Radford et al. designed an approach to stabilize GAN. This approach was beneficial to overcome with small dataset overfit problem in CNN and ML.

To enhance the image resolution, SRGAN is one of the well-known approaches used widely. In this approach, the generated image has a higher pixel resolution; some of the known works using SRGAN were conducted in 2016 by Christin Leidg et al. [30] and in 2017 by Huang Bin et al. [31]. In 2018, Subeesh et al. [32] presented an approach to creating a high-resolution image for photographs using the SR network.

The GAN model can also be applied to generate pictures of human faces. In 2017, Tero Karras et al. [33] published a work where celebrity faces are generated from input samples, and the generated output is quite similar. Later many works were published using Tero Karras et al. work as a base paper.

The image-to-Image translation is a vital application of image translation research using GAN. The first paper on image translation was published in 2016 by Philip Isola et al. [34]. The work was proposed on conditional adversarial Network and pix2pix approach. In 2018, Andrew Brock et al. [35] proposed a work to generate realistic photographs using bigGAN. It is noticed the generated images are very similar to the old photos with better accuracy. Face frontal view generation by GAN came to light in 2017 by Rui Hang et al. [36]. The global and local GAN is used in this paper. The face photos taken from various angle is used to generate the different frontal view and human poses.

To analyze the growth and advancement of GAN in various fields, we have queried across the different journals with a keyword "GAN" and "Generative Adversarial Network" with a filter of publication year from 2016 to 2023. This search aims to give a detailed, comprehensive overview for researchers and practitioners where we can answer the following research questions based on the growth of GAN, as shown in Table 1. In Table 2, CONF: Conference, JOR: Journal, EAA: Early Access Article, MAG: Magazine, BOK: Book, RA: Review Article, RSA: Research Article, BOC: Book Chapter, COP: Conference Proceeding, RWE: Reference Work Entry and RW: Reference Work.

After analyzing research questions, we understood that the progress of GAN in various domains is increasing exponentially, especially in computer vision, as observed in RQ5 in Table 2. This paper aims to analyze and understand current practices, approaches and ground truth of GAN in computer vision and image enhancement techniques. Our contribution to this paper is as follows:

- A detailed literature survey on GAN and its variants is carried out. The detailed report on the technique and the current tool is outlined by framing the research questions.
- A detailed review of existing work in image enhancement techniques in GAN is discussed. Depth analysis of evaluation metrics, datasets, methodology and tools of various methods are explained in detail by carrying out a systematic literature review.
- We highlighted some of the gaps and challenges in the spectrum of image enhancement techniques using GAN, which can be helpful for future research work.

Overall, this paper is structured as follows, in Sect. 2, the detailed review process is presented by defining the research question. In Sect. 3, variants of GAN in computer vision and outcome of research questions are outlined; Sect. 4, gaps and challenges are discussed, and in Sect. 5 conclusion.

2 Taxonomy of Systematic Literature Review

To perform a detailed and systematic literature survey, we have referred few benchmark review works proposed by Bugen et al. [37], B Kitchenham et al. [38] and M. A Barbar et al. [39] in the area of software engineering. Throughout this paper, we have taken up their approaches to design our review and manifested our survey into three significant steps planning, conducting, and reporting, as shown in Fig. 4.

2.1 Planning

The primary aim of this stage is to give sufficient information and give a systematic path for the conduction and reporting stage. This phase consists of three steps.

Table 1 Defined research question to analyze growth of GAN in various field

No.	Research question
RQ1	How is the research growth of GAN in various Domain?
RQ2	How many numbers of publication available on GAN in computer vision?
RQ3	How is the increase in publication count on GAN in cyber security?
RQ4	How is the scope for GAN in Healthcare?
RQ5	How is research growth of GAN in computer vision?

Table 2 Distribution and growth of research works in GAN across various journal that satisfy defined research questions

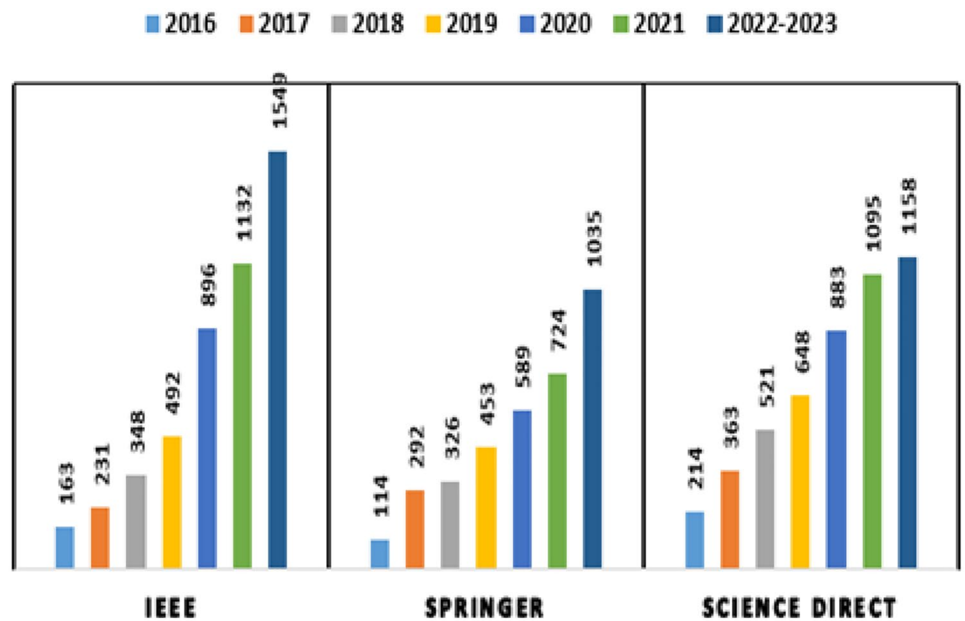
Research question	Keywords used for search	Total publication [2016–2023]	Category	Outcome
RQ1	GAN, Generative Adversarial Network	**IEEE:**4811	CONF:3255	
			JOR: 1359	
			EAA: 80	
			MAG: 15	
			BOK: 2	
		Springer: 5353	CONF: 1195	
			BOC: 1669	
			BOK: 792	
			RSA: 1128	
			COP: 553	
			RWE: 12	
			RW:4	
		Science Direct: 4882	RA: 523	
			RSA: 4176	
			BOC:183	
RQ2	GAN in computer vision, Generative Adversarial Network in Computer Vision	**IEEE:**1716	CONF: 1375	Till date [From 2016–2023], total 6170 research publication are retrieved from IEEE, Springer and Science Direct using the keyword
			JOR: 311	
			EAA: 23	
			MAG: 5	
			BOK: 2	
		Springer: 1980	BOC: 632	
			COP: 416	
			RSA: 398	
			BOK: 304	
			COP: 230	
		Science Direct: 2474	RSA: 2324	
			RA: 150	

Table 2 (continued)

Research question	Keywords used for search	Total publication [2016–2023]	Category	Outcome
RQ3	GAN in Cyber Security, Generative Adversarial Network in Cyber Security	**IEEE:**174	2017: 42 2018: 110 2019: 244 2020: 307 2021:327	According to the survey, every year, remarkable exponential growth is observed in the count of research papers on Generative Adversarial Networks in Cyber security
		Springer: 666	2022–23:411	
		Science Direct: 601		
RQ4	GAN in Healthcare, Generative Adversarial Network in Healthcare	**IEEE:**1274	CONF: 834 JOR: 403 EAA: 32 MAG: 4 BOK: 1	After querying in IEEE, Springer and Science Direct using the keywords, the total number of papers available to date is 3583 research works. And we received 29 publication topics on GAN in healthcare. Hence, there is a scope for GAN in healthcare
		Springer: 666	BOC: 412 COP: 311 RSA: 252 BOK: 232 COP: 173	
		Science Direct: 1643	RSA: 1523 RA: 120	
RQ5	GAN in computer vision, Generative Adversarial Network in Computer Vision	**IEEE:**1716	2017: 71 2018: 182 2019: 327 2020: 339 2021:371 2022–23:426	It is observed every year there is an exponential growth in number of papers available on Generative Adversarial Network in Computer Vision

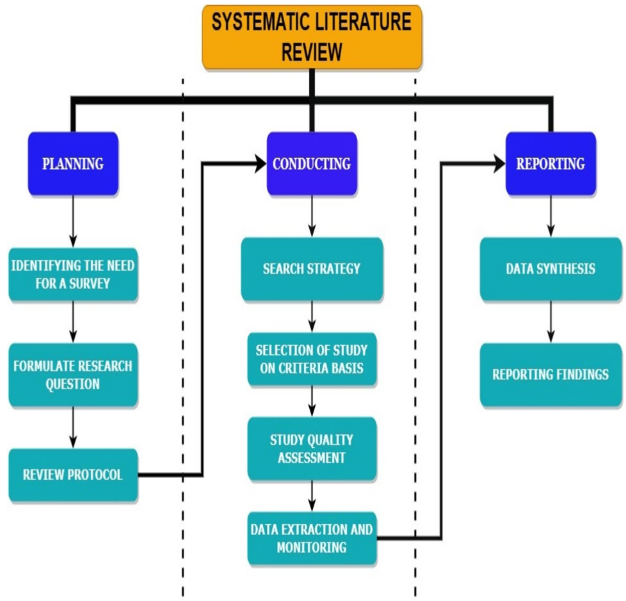


Fig. 4 Taxonomy of Systematic Literature Review

- Identifying the need for a Survey
  Before a systematic survey, the research scholar must understand how important the survey is. The researcher should undergo existing survey work available, and we have read a good count of work to perform this step.
- Formulate Research Question
  A well-structured research question will help to understand the identified study in a proper direction. We have drawn all possible research questions in this phase to match our study.
- Review Protocol

Generally, protocols are the critical element in most of the literature survey. Analyzing the described research question, planned strategy, and background context meet the designed survey or not is executed in this step. In this study, we have followed a hierarchical approach to review protocol.

2.2 Conducting

Conducting is the next step after the planning. In this phase, there are four steps.

- Search Strategy
  It is a predefined approach that aims to find possible primary research papers related to our work. In this step, we designed a search technique based on a specific keyword, a synonym of a keyword or a constructed string using possible keywords.
- Selection of Study on Criteria Basis
  Various challenges are encountered during the literature selection process, like language, author, journal etc. The presented work follows a well-defined protocol to decrease bias and ensure fairness.
- Study Quality Assessment
  This process's primary goal is to ensure the quality and relevance of selected papers from the previous steps. Here, we have fixed a set of quality metrics to appraise the quality of this study.
- Data Extraction and Monitoring
  In this phase, the source and form used to collect the required data for the study are designed. We have carefully selected the necessary references and entities in our research and well-recorded them.

2.3 Reporting

In this phase, all the extracted and analyzed data is summarized well. This phase consists of two steps.

- Data Synthesis
  In this step, data synthesis and summarization are achieved using a graphical and tabular approach, which is more suitable for understanding.
- Reporting Finding

In this stage, the synthesized data is reported in the proper channel that can target research scholars and evidence.

2.4 Implementation of Systematic Literature Review

2.4.1 Identifying the Need for a Survey

To identify the importance of the study, we tried to analyse the current research trend, especially in GAN. We have searched various journals, and it is observed there has been a steady growth in the count of papers published over the years, as shown in Table 2.

2.4.2 Formulate Research Question

Picking a research question is an essential first step to define the overall purpose of the specific study. In this paper, we have established stable research questions (RQ) to guide researchers, increase confidence in the domain and understand the recent exercise and trend of GAN in computer vision. The established RQs and SRQs are given in Table 3.

2.4.3 Review Protocol

After defining the RQs, the research questions are sent to the research guide, research supervisor and co-supervisor to check the depth and correctness of the RQ. The research guide has also evaluated the protocol design of this study. After reviewing the protocol from the supervisor, we proceeded further in our research.

2.4.4 Search Strategy

We have started our research with the intent to compile as many studies and work related to our research domain. In this phase of the collection, we included all possible keywords and also phrases that match the keywords. The possible keyword used is shown in Table 4.

To collect the study papers, we looked into several journal repositories. However, many digital journals are available these days; the selected journals for this paper are listed below.

- Web of Science
- IEEE digital library
- ACM digital library
- Springer
- Semantic Scholar

This search is restrained to the period of 2014 to 2023, including journals, conferences and archives.

2.4.5 Selection of Study on Criteria Basis

In selecting the relevant work after the search and collection process, we established two inclusion criteria to pick the most relevant study, as listed below.

- The keyword should be part of the abstract, keyword and title.
- Few papers have worked in GAN and do not involve the keyword in the abstract, title and keywords. We have gone through the complete article to complete the selection process in such cases.

To skip some studies that do not support the objective and aim of the study, we have defined three exclusion criteria as follows.

- Studies which are not in English.
- GAN papers related to healthcare, cyber security, networks and other domains unrelated to computer vision.
- Conference proceedings are not considered for the study.

The detailed inclusion process is shown using the PRISMA approach in Fig. 5.

2.4.6 Study Quality Assessment

After the selection process, accessing quality proof is crucial to conduct a proper systematic review. The result obtained

Table 3 Defined research question to perform systematic literature survey

QNO	Research question	Justification
RQ-1	What are the well-known variants of GAN?	Describe all the possible variants of GAN
SRQ-1.1	What are the frameworks available to work with GAN?	Identify different frameworks to work with GAN variants
SRQ-1.2	What are the applications of different types of GAN?	List application of each GAN variant
RQ-2	What are the well-known approaches for image enhancement techniques using GAN?	Describe different approaches that support image enhancement techniques using GAN
SRQ-2.1	Which are the datasets typically used in image enhancement by GAN?	Find the dataset that is used in existing work
SRQ-2.2	What are the models used in image enhancement techniques using GAN?	Categorize commonly used models in existing work
SRQ-2.3	What are the metrics used to evaluate image enhancement using GAN?	List the evaluation metrics used in existing work
RQ-3	Whether GAN is a better approach for image enhancement? How is image enhancement performance in GAN, MATLAB and other platforms for image enhancement?	Perform a comparative analysis of results

Table 4 Various keywords used in search strategy

Keyword 1	"Generative Adversarial Network" OR "GAN"
Keyword 2	"GAN in computer vision" OR "GAN in image processing"
Keyword 3	"Image enhancement using GAN" OR "Image enhancement using Generative Adversarial Network" OR "Image clarity improvement using GAN"
Keyword 4	"Types of Generative Adversarial Network" OR "GAN variants"

from the survey should be firm and avoid all sorts of bias. This paper uses the criteria stated in research work [40] to analyse the quality assessment.

2.4.7 Data Extraction and Monitoring

In this phase, we will extract the data required for the study. After going through six journal repositories to answer the defined RQs, we have set some rules and minimal entities required from each paper. In this paper, we extracted author details, publication details, journal details, dataset, features, methods, and metrics used.

2.4.8 Data Synthesis and Reporting

The data synthesis and reporting is the last phase of the systematic review, where the findings from the data extraction stage are segregated and presented as a supportive definition for RQs. In this phase, we have used graphs and tables to visualize the summarized data.

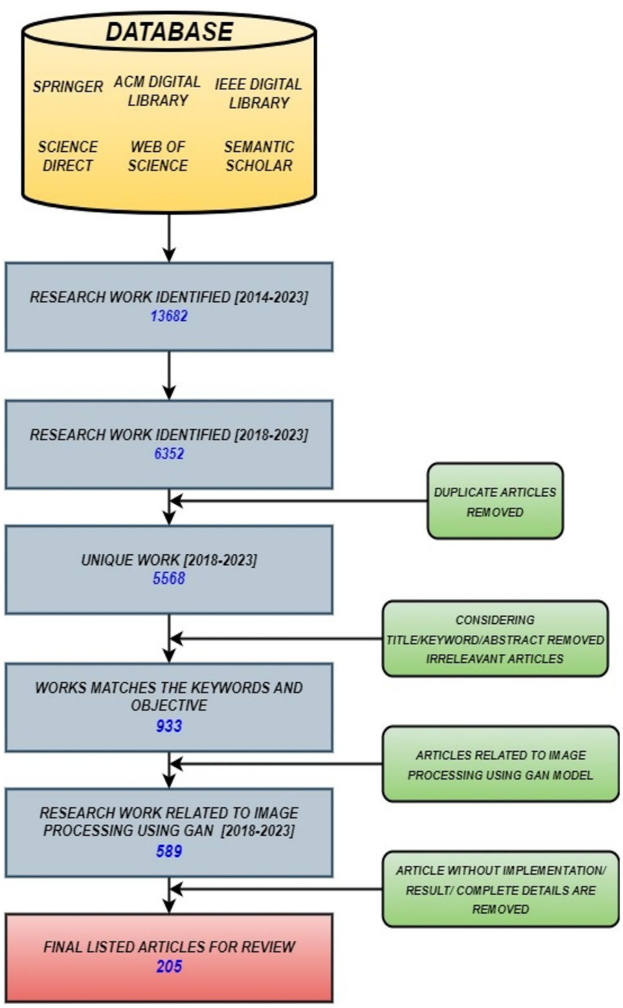


Fig. 5 Prisma Inclusion Process for Systematic Literature Review

3 Outcomes

3.1 RQ-1: What are the Well-known Variants of GAN?

3.1.1 Deep Convolutional Generative Adversarial Networks (DCGAN)

The DCGAN layer model was proposed by Radford et al. in 2015, in which they presented two CNN models, namely discriminator and generator with a convolution transpose layer as shown in Fig. 6.

The principal aim of DCGAN is to support unsupervised learning using stride and transposed convolution for down-sampling and upsampling[66].

The essence of DCGAN is as follows:

- Eliminates all hidden layers.
- Max pooling layers are replaced with the stride convolution layer and fractional stride convolution layer in the discriminator and generator, respectively.
- Batch normalisation is used, except for the generator's output layer and the discriminator's input layer.
- Leaky ReLu is applied in all layers of the discriminator.
- ReLu is used in the generator except in the output layer. In the generator output layer, tanh is applied.

In this paper, some of the work based on DCGAN are presented. In the survey process, our foremost aim is to identify the methodology, model and application where DCGAN can be applied. In [41], Yurika Sagawa et al. presented a model for facial image generation using attributes and labels by DCGAN, and a few more works are noticed where researchers' primary motivation was to generate a facial image using DCGAN in [44, 46, 53, 58, 61].

The DCGAN gives a higher contribution in data augmentation to enhance any target CNN model's accuracy by increasing the dataset's size or building a training model, as seen in [52, 59]. However, the most noticeable work of DCGAN is in creating and performing analysis of Anime Characters [61, 63]. It is noticed using the DCGAN with the CNN model or some well-known algorithm like self-learning [58], SVM [46] etc., will give better accuracy. The detailed study of DCGAN is outlined in Table 5.

3.1.1.1 SRQ-1.2: What Are the Applications of DCGAN? Based on the applications of DCGAN in computer vision, we noticed the higher contribution of DCGAN is marked in image generation and data augmentation. Considering all 25 works together,

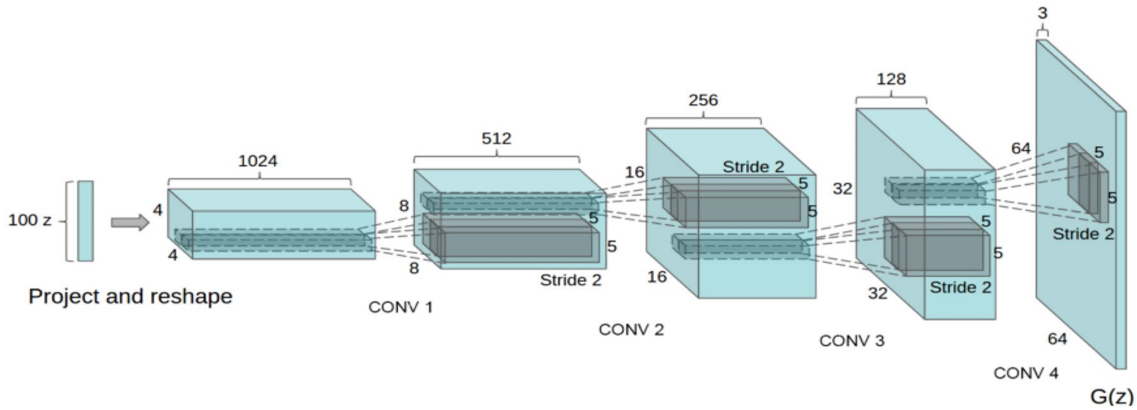


Fig. 6 Proposed DCGAN Model In [66]

we observed five papers specially used for face image synthesis, six on data augmentation, two on anime character generation, four on resolution enhancement, and eight on data generation. Table 5 illustrates a detailed study of 25 research papers on DCGAN; based on this table, Fig. 7 outlines a list of DCGAN applications. Hence it concludes DCGAN works fine in situations of image generation.

3.1.2 Conditional Generative Adversarial Networks (CGAN)

Conditional GAN (CGAN) is a novel approach and a well-known variant of GAN designed to train generative models. The first glance of CGAN was in 2015, presented by Mehdi Mirza et al. [67].

The primary function of conditional GAN is to learn samples from distribution instead of sampling from marginal distribution. In conditional GAN sampling is based on additional auxiliary information like labels and data. The detailed architecture is given in Fig. 8. Based on Fig. 8 the 2-player min–max function v(G, D) given in [29] can be redefined for CGAN as shown below.

$$\min_G \max_D V(D,G) = E_{x\ pdata(x)}[\log D(x)] + E_{z\ p(z)}[\log(1 - D(G(z)))] \tag{2}$$

Here D(xly) is the discriminator with x input and y label, and G(xly) is the generator with noise vector and y label.

Generally, the major applications of CGAN are video generation, face generation, Image-to-Image Synthesis and Text to Image Synthesis. When we queried IEEE digital library with the keyword CGAN and filtered from 2019 to 2023, 24 publication topics were listed; in the extracted list, image classification, feature extraction, and medical image processing are the top 3 publication topics for CGAN. In this study, we have received 34 papers on CGAN by restricting our subject to CGAN in computer vision and image processing. The detailed outline of the studied research papers is given in Table 6.

In the survey phase, we came across various works; among these, image processing in the medical field using CGAN has many notable results. In [68], Changhee Han et al. used 3D Multi conditional GAN to augment a small fragmented CT image dataset. Similar works are observed in Ke Xu et al. [69] and Meng Li et al. [70], presenting a novel approach of CGAN named MCRGAN with the capacity to generate pseudo-CT images under limited training dataset conditions and transform-based architecture CGAN called MedViTGAN for augmentation of synthetic histopathology image. In the medical field, one more application of CGAN is image segmentation. In [71, 72], we noticed the application of CGAN in improving lesion contrast of MR images and retinal vessel segmentation. Image denoising by Zhao Yang et al. [73],[74]and Miao Tian et al. [75], Image synthesis by Huan Yang et al. [76], Zhaohui Liang et al. [77] and Yulin Yang et al. [78] are some of the noticed works of CGAN in image processing for the medical field.

Apart from medical image processing, we have studied the application of CGAN in the computer vision domain. In Jeongik Cho et al. [79], CGAN increases hyperparameters and reduces training speed. The designed approach uses multiple GANs, sharing all the hidden layers. In [80], the work presented by Tetsuya Ishikawa et al. illustrated a method to augment training data using CGAN. Few works in computer vision addressed problems like large model size and high interface time [81], and in [82], Felipe Coelho Silva et al. demonstrated a semi-automatic frame for manga art colourization. The other application of CGAN is in quality reconstruction, Art font, image generation, video games, rejuvenation of face image etc. In Table 6, we have given a comparative analysis of all our studies in CGAN based on parameters like purpose, model and outcome.

Table 5 Comparative study on DCGAN model

Author and year	Problem addressed	Approach	Outcome
Yurika Sagawa et al. [41], 2018	Develop attribute added face generation system	Attribute extraction- CNN Enhancing resolution—DCGAN	Similar Person Score-49.2
Juping Zhong et al. [42], 2019	Recognition of street house number	Feature Extraction-CNN Face image generation -DCGAN	Model become stable as the training increase
Daeun Dana Kim et al. [43], 2020	Generation of labeled pedestrian dataset	DCGAN	As training increase realistic in generated image increase
Bingqi Liu et al. [44], 2022	Image Generation	Improvised DCGAN	Problem of gradient disappearance solved Image quality is improved DCGAN value is 2.02 higher than normal GAN
Mohammed A B mahmoud et al. [45], 2019	Recognition of traffic signal	Feature Extraction-DCGAN Classification- multilayer perceptron neural network, pseudo inverse learning autoencoder	Better result compared to existing work Recognition rate-99.72%
Li Sun et al. [46], 2021	Apple quality classification method	Image segmentation -SVM Data Expansion -DCGAN, Improved RSNet	Classification Accuracy -96.5%
Xiuhong Yang et al. [47], 2021	Restoring missing and damaged face area	Improvised DCGAN encoder and Decoder Generation Local and Global adversarial discriminator	PSNR—26.28 SSIM—0.8954
Jiacheng Xu et al. [48], 2021	Tackle block effect problem in geometry compression	3D AE-DCGAN	Increase in the mean BD-PSNR by 1.325 dB and 4.55 dB respectively
Qiufeng Wu et al. [49], 2020	Data augmentation for tomato leaf dataset	DCGAN	Accuracy-94.33%
Moktari Mostafa et al. [50], 2021	Enhancing cross spectral resolution Iris recognition	DCGAN, CGAN and CPGAN: To enhance maximum pairwise similarity between future	Recognition accuracy have lower EER value of 1.5%
Nandini Kumari et al. [51], 2021	Enhancing the clarity of reconstructed image using ImageNet	Pre-trained model using DCGAN	Lower the loss between generated and real image
WenHao Li et al. [52], 2020	Noise reduction for structured light	DCGAN to generate dataset Autoencoder to denoise the structured light	Robustness is increased and noise is decreased
Kai Wu et al. [53], 2020	Data augmentation of faces in campus data	Rotate and Render DCGAN	Accuracy rate is 97.6%
Sung Nien Yu et al. [54], 2022	Improving of distinguish ability in Emotion recognition	RSNet, DCGAN	Accuracy rate 90.34%
Taizhi Lv et al. [55], 2020	Improve the accuracy of face detection	CNN with local binary pattern and DCGAN	Recognition Accuracy 85%
Kunwang et al. [56], 2020	Recognition of object in night scene	DCGAN: To generate day image same as night Faster R-CNN- feature fusion and multiscale ROI detection	MAP = 82.6%
Qiushi Sun et al. [57], 2022	Synthesis of face image from facial part	Deep Learning and DCGAN	PSNR:34.38% SSIM:0.956%
Shawi R. E et al. [58], 2022	Patch based breast cancer classification	Semi Supervised DCGAN and self learning technique	Accuracy: 77.3% F-measure: 85.72
Sayeda Samia Nasrin et al. [59], 2020	Henna art design generation	DCGAN	Better than existing work
Christine Devis et al. [60], 2021	Traffic sign recognition for image generation by GAN	DCGAN, LSGAN, WGAN	LSGAN proved better with 84.9% accuracy
Zecheng Li et al. [61], 2021	Anime character generation	DCGAN	Image with better quality and accuracy
Xiuhong Yang et al. [62], 2021	Semantic face generation	DCGAN and dual discriminator	Better accuracy

Table 5 (continued)

Author and year	Problem addressed	Approach	Outcome
Yifei Jiang et al. [63], 2021	Anime character generation with performance analysis	DCGAN with GUI	Image with better quality and accuracy
Mingyu Qiao et al. [64], 2021	Data expansion flower dataset	DCGAN and RSNet classification	Accuracy is significantly improved
Wang Tin Fe et al. [65], 2021	Image in-painting using ISAR algorithm	DCGAN: Image Quality ISAR imaging algorithm	PSNR:28.51 SSIM: 0.90

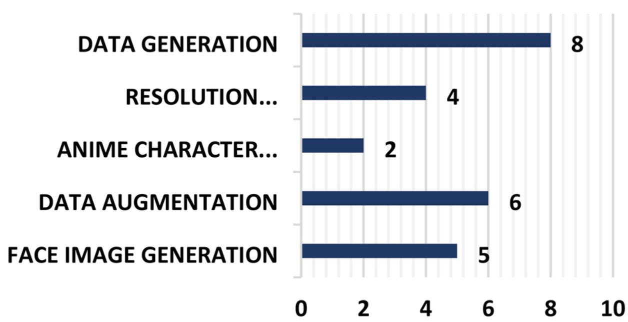


Fig. 7 List of Applications Used In DCGAN

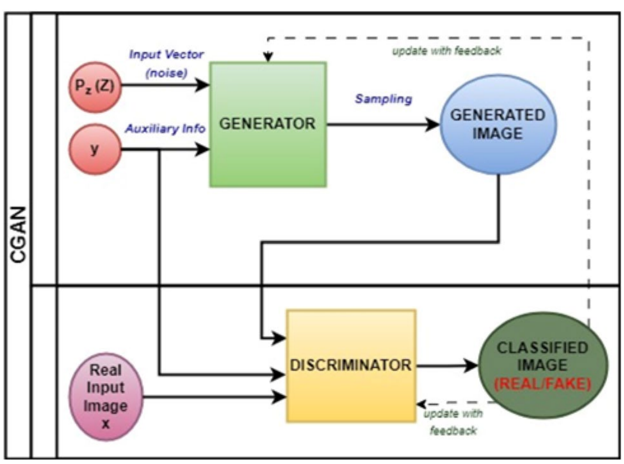


Fig. 8 Conditional GAN Model

3.1.2.1 SRQ-1.2: What are the Applications of CGAN? After studying 34 research works on CGAN in computer vision, we recorded Image to Image Synthesis is one of the well-noted applications. Considering the application and purpose of all 34 works, a detailed pictorial view is given in the graph of Fig. 9. From Fig. 9, we can conclude Image to Image Synthesis, Image Enhancement and Text to Image Synthesis are some of the applications where CGAN can definitely be used.

3.1.3 Cycle Generative Adversarial Networks (CYCLEGAN)

CycleGAN is another noteworthy variant of GAN presented in 2017 by Jun-Yan Zhu et al. [102]. The principal objective of the model is to map the images without paired data using the mapping function G(x- > y) and an adversarial loss function.

The image generates from the first generator, G(x), is similar to y, that is, G(x- > y) = > y = G(x). Moreover, in this approach using inverse mapping, y will learn from x that is F(y- > x) = > x = F(y). It can be said F(G(x)) = x and G(F(y)) = y using inverse mapping and cycle consistency loss. The pictorial representation of the Cycle GAN methodology is given in Fig. 10.

During the training process, Cycle GAN focuses more on the training dataset and follows a few practices as follows.

- The training set paired image {xi,yi} where all xi in a dataset has yi as its counterpart.
- The training set paired image {xi,yi} where every xi in the dataset dont have any match with yi.

To get a broad view of CycleGAN and its methodology, we have surveyed more than 25 research papers. The significant observation is that CycleGAN is majorly used for Image Synthesis, especially in the medical field. In Taesung Kwon et al. [103] and Jawook Gu et al. [123], image synthesis is used for denoising low-dose CT images. CycleGAN is also used for augmentation purposes in the classification of Melanoma medical images when a limited labelled dataset is available for training purposes[104]. ECG restoration [104] and fundus image enhancement in diabetic retinopathy classification [112] are the other recognized applications of CycleGAN in medical image processing. Moving apart, if we consider the general application of CycleGAN in computer vision, SAR to optical image registration [106, 120], NIR to RGB image [116] and VIS to NIR image [117] are the maximal noted research works. Along with this, image colourization, denoising and image enhancement in low light and night images are the few other works observed. A detailed study of Cycle GAN is given in Table 7.

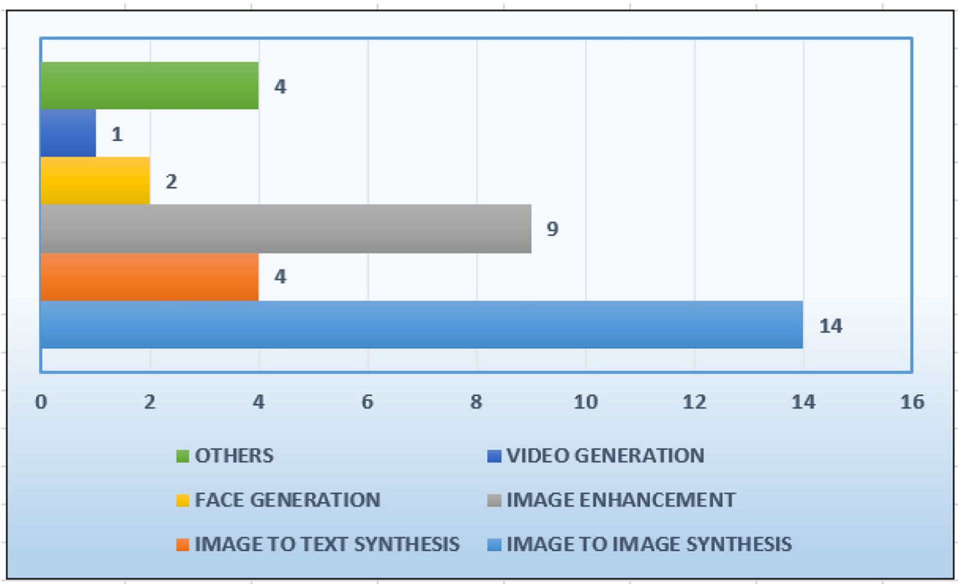
Table 6 Comparative study on CGAN model

Author and Year	Problem Addressed	Approach	Remarks
Changhee Han et al. 2019 [68]	3D multi conditional GAN to generate realistic CT image to enhance performance of 3D object detection	MCGAN with two discriminator and faster RCNN	Fixes the false positive rate
Duc Minh Vo et al. 2022 [89]	Designed a model for large CGAN compression	PPCD-GAN every convolution layer is continued by learnable mask layer	Efficient parameter reduction and speed increase
Yitong Li et al. 2019 [96]	Sequence image generation for story visualization using multi line paragraph	Sequence of CGAN with deep context encoder and two discriminator	Visual Quality-74.17 Consistence- 79.15 Relevance—7808 and its better than existing approach
Prarabdh Raipurkar et al. 2021 [100]	Adding details to over exposed saturated region image	CGAN	PSNR-17.57 SSIM- 0.78
Yingxue Zhang et al. 2020 [101]	Identifying traffic estimation based on time slot	CURB GAN based on GAN	Shows 52.77% RMSE and 55.38% MAPE value improvement
Mateus C Silva et al. 2021 [99]	Defoliation and leaf shape estimation	Unet based conditional GAN using Otsu Method	Damage estimation value- RMSE = 2.09
Sharada Murali et al. 2019 [93]	Transforming style and design from one data set to another data set using CGAN	Multiple conditional input GAN with an ability ti input iamge and class lable	LPIPS = 0.5883
Miao Tian et al. 2021 [75]	Enhancing image denoising in MRI image	CGAN	SSIM—0.94 Better SSIM and robustness
Ye Yuan et al. 2020 [91]	Generation of art font	CGAN with typeface and ornament network	High quality image are generated
Mingyi Chen et al. 2018 [97]	Synthesis of facial expression	Double encoder conditional GAN to change original and target expression using associative learning	Satisfactory result compared to existing work
Ruben Rodriguez Torrado et al. 2020 [90]	CGAN bootstrapping for level generation in video game	Conditional Embedding Self Attention GAN with a an approach to condition the training of generator and discriminator	Reduce the number of level required for training
Jeongik Cho et al. 2020 [79]	Improved ACGAN	CAGAN to improve ACGAN batch normalization and consistency in real and generated data	Training speed is improved and hyperparameters are reduced
Huan Yang et al 2019 [76]	Generate multi contrast MRI image	CGAN	Preserve high frequency PSNR—20.68
Muyang Li et al. 2020 [81]	Reducing model size and interface time of generator in CGAN	CGAN with neural architecture search	Many CGAN variants can be compressed without loosing visual quality
Miran Heo et al. 2019 [92]	Reflection removal	Preserving low and high frequency detail using CGAN	PSNR—20.20 SSIM—0.7257
Zhaohui Liang et al. 2020 [77]	Generation of COVID-19 chest X- ray from normal chest X- ray	CGAN with optimization architecture	Accuracy- 0.96
Tahmida Mahmud et al. 2018 [88]	Reconstruction of missing frame using CGAN	CGAN	PSNR—35.03 SSIM—0.93
Vu Nguyen et al. 2017 [98]	Shadow detection in single image	CGAN with additional sensitivity parameters	17% error reduction compared to existing work

Table 6 (continued)

Author and Year	Problem Addressed	Approach	Remarks
Felipe Coelho Silva et al. 2019 [82]	Semi automatic framework for coloring Manga concept art	CGAN with hint-based line-art colorization technique	Still need to be improved compared to existing work
Mohammad Hamghalam et al. 2020 [71]	Improving the contrast of brain lesion image	CGAN with novel generator and Markovian discriminator	PSNR – 22.33 SSIM – 0.7245
Ang Nan Gu et al. 2021 [83]	Acquisition framework to give predictive echo view of heart	Constrained conditional GAN	84% correlation observed between generated ground truth and segmentation mask area
Xiaodong Liu et al. 2020 [95]	Color correction for underwater images	CGAN with multi scale feature fusion discriminator and Patch GAN	PSNR—22.00 MSE—0.0055
Kang Liao et al. 2020 [87]	Rectification of radial distortion	CGAN trained by low to high perceptual loss and various structural image mapping	Better PSNR and SSIM value compared to existing approach
Li Tao et al. 2018 [84]	Automatic generation of attenuation map from MR image	Novel CGAN approach by combining generator and discriminator loss	Pixel prediction error reduced by 50%
Ke Xu et al. 2019 [69]	Pseudo PCT generation for MR images	MCRCGAN, ResNet + GAN	Quality of PCT generation increased
Kyeongjin Ann et al. 2021 [85]	Overcome class imbalance problem in CXR dataset	Class activation region influence maximization conditional (CARIM-cGAN)	Probability of diseases occurrence in bounded region is increased and generation cost reduced
Jingkuan Song et al. 2022 [94]	Rendering and personality preservation in face aging	Dual conditional GAN—AGE GAN + + by sharing the weight with dual and primal part of steamline	Better performance compared to existing approach
Zhao Yang et al. 2021 [73]	Denoising CT image	CGAN with structural loss based on unpaired data	Efficient denoising performance
Mateus Baltazar de Almeida et al. 2021 [74]	Low dose CT image denoising	GRC-GAN using network gates	Focuses more on denoising compared to existing works
Chufu Deng et al. 2021 [86]	Image translation framework to translate from MRI to other image	CGAN with one hot vector and GRAD-CAM	Better performance compared to existing approach

Fig. 9 List of Applications Used



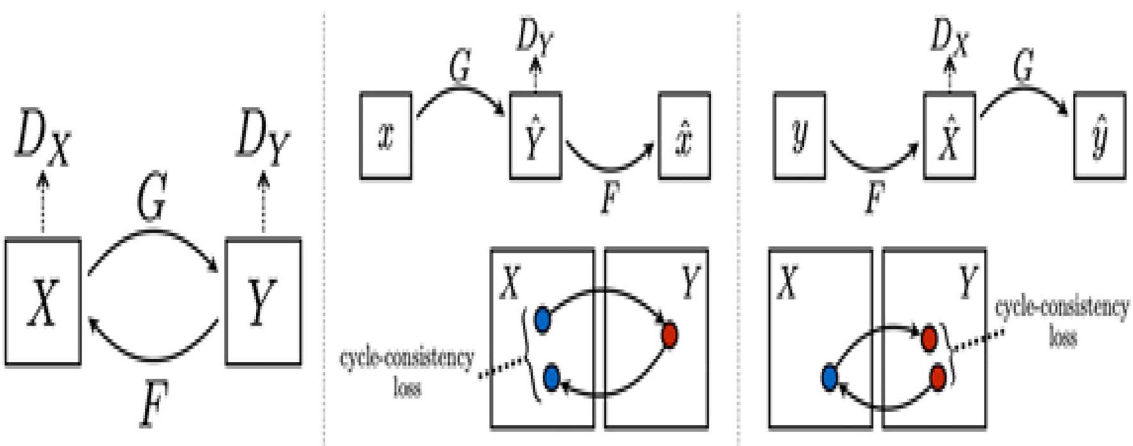


Fig. 10 Cycle GAN Training Process [101]

3.1.3.1 SRQ-1.2: What are the Applications Of CycleGAN? Based on the research and problem addressed in the state of art methods from Table 7, we collected some of the following basic observations. Firstly, CycleGAN is majorly used in Image Synthesis for unpaired data in various domains. Secondly, using CycleGAN, training time and memory consumption can be reduced. At last, CycleGAN is also helpful for converting any existing supervised method to an unsupervised one. The detailed usage of CycleGAN is given in Fig. 11.

3.1.3.2 Style Generative Adversarial Networks (STYLEGAN) StyleGAN is a variant of GAN introduced by Tero Karras et al. in 2019 [134]. It is the first variant of GAN focused on the advancement and improvement of the generator, then the discriminator. This model is built with two networks, namely the mapping network and the synthesis network. The StyleGAN inputs the latent space vector directly into the mapping network, which comprises eight fully connected layers. The output of the mapping network is later sent to the synthesis network architecture consisting of 18 convolution layers and an AdaIN style network.

The synthesis network produces 4 × 4 to 1024X1024-sized images in every layer. Gaussian noise is added to the activation map before sending the images into the AdaIN method. And this is the primary reason that StyleGAN can produce high-resolution images. The comphrehensive architecture of StyleGAN is shown in Fig. 12.

The significant changes and updation in the StyleGAN compared to other GAN architecture are as follows.

- Tuning and bilinear upsampling are added.

Table 7 Comparative study on CycleGAN model

Author and Year	Problem Addressed	Model	Outcome
Taesung Kwon et al. 2021 [103]	Cycle GAN for fast denoising low dose CT without using multi generator and discriminator	Cycle GAN with invertible generator with cycle consistency function	Only 10% learnable parameters are used with fast training
Xiyan Liu et al. 2018 [104]	Image Synthesis without loosing original image and attributes	Two coupled adversarial network with cycle consistency loss	Can learn semantic information from text and high training speed
Yixin Chen et al. 2020 [119]	Data augmentation using CycleGAN for melanoma images	CycleGAN and EfficentNet B1	Cost of manual annotation decreased and accuracy—0.945
Xuejun Huang et al. 2020 [106]	Registration of optical and SAR images without radiometric and geometric difference	Improved CycleGAN—SAR images are converted to Pseudo optical images	Registration performance is increased
Hongqian Chen et al. 2021 [107]	Transferring of style to unpaired fruit images	ArCycleGAN: Registration of attribute in CycleGAN	50% training dataset and 5.8% time is reduced compared to existing work
Serkan Kiranyaz et al. 2022 [108]	ECG restoration by removing artifacts and noise	CycleGAN with 1D operational function and generative neuron model	Precision-95.84 Recall-96.53
Junzhuo Liu et al. 2022 [109]	Overcome insufficient clinical dataset problem by data augmentation	Self-attention branch, self attention loss and mask loss function are added to generators of CycleGAN	Accuracy-0.89
Hyo Sik Yoon et al. 2020 [110]	Deblurring of motion blurred images in vehicle environment	CycleGAN	PSNR-24.94 SSIM-0.88
Fengquan Zhang et al. 2020 [111]	Image translation by preserving semantic information	CycleGAN with AdaIN framework	PSNR-8.91 SSIM-0.91
Qijing You et al. 2019 [112]	Fundus image enhancement in retinal image	CycleGAN with convolution block attention module	PSNR-19.27 SSIM-0.68 Visually images are better with less noise
Yu Hwan Kim et al. 2020 [113]	Image transformation without age class imbalance	Enhanced CycleGAN	Better performance compared to existing system
He Zhu et al. 2021 [114]	Multistep Fakesafe mapping	CycleGAN	Better human level steganography compared to existing work
Xiaotao Shao et al. 2020 [115]	Night time vehicle image enhancement	CycleGAN with feature translate enhancement and object detection module—FteGanOd	Detection Rate = 97.8%
Hao Dou et al. 2019 [116]	Translating near infra red face to RGB face	Asymmetric CycleGAN with U-net	Image quality is enhanced compared to existing approach
Huijiao Wang et al. 2020 [118]	VIS Image to NIR Image translation	Facial feature embedded CycleGAN	Accuracy—96.5%
Xiaoxia Xiao et al. 2020 [117]	Generating pedestrian image targeting particular pose	CycleGAN with a Network designed in loop structure using 2 discriminator and generator	Generate images are little fuzzy due to low clarity source image
Xiyan Liu et al. 2018 [104]	Image synthesis using text	Conditional CycleGAN	Better performance compared to existing system
Jieon Hwang et al. 2020 [120]	Translation of SAR Image to Optical Image	Cycle consistent GAN with two generator and two discriminator	(VGG + SSIM) = (9.84/0.22)
Gyutaek Oh et al. 2020 [121]	Accelerated MRI sensing without labelled data	CycleGAN using dual formulation	Better generalization power
Se Woon Cho et al. 2020 [122]	Segmentation approach for low light and night images	Modified CycleGAN by altering residual blocks	PSNR = 22.73 SSIM = 0.67

Table 7 (continued)

Author and Year	Problem Addressed	Model	Outcome
Jawook Gu et al. 2021 [123]	To overcome additional memory requirement and increase in number of learnable parameter in CycleGAN	Tunable CycleGAN using AdaIN	PSNR = 30.87 SSIM = 0.66
Xin He et al. 2022 [124]	Dehazing unsupervised model for Aerial Images	Asymmetric Contrastive CycleGAN	PSNR = 24.35
Xiaoxuan Lv et al. 2019 [125]	Conversion of Chinese style classical landscape painting into photo	CycleGAN with L2 loss	Satisfactory result
Amirhossein Sanaat et al. 2020 [126]	PET low dose image synthesis	CycleGAN + ResNet	PSNR = 39.08 ± 3.56 SSIM = 0.97 ± 0.02
Guang Li et al. 2021 [127]	Colorization of SAR image	multidomain cycle-consistency generative adversarial network	Designed model gives effective result
Anil Singh Parihar et al. 2021 [128]	Quality enhancement of low light images	CycleGAN	Perceptually and quantitatively gives better result
Tong Su et al. 2021 [129]	Translation of visible image to infrared image	ES-CycleGAN	Better PSNR and SSIM value
Mingyu Yang et al. 2021 [130]	Style transfer between the images	CycleGAN with dual path network	SSIM increased by 3.6%
Selma Guzel et al. 2022 [131]	IR image generation from RGB images	CycleGAN	Success rate of CycleGAN is increased
Ai Takahashi et al. 2019 [132]	Fingerprint domain transformation	CycleGAN	Fingerprint recognition accuracy increased
Jung Hoon Lee et al. [133]	Colorization of SAR image	CycleGAN	PSNR—20.0728

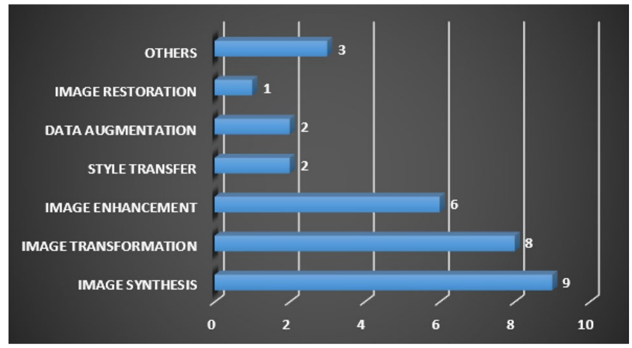


Fig. 11 List of Applications used in CycleGAN

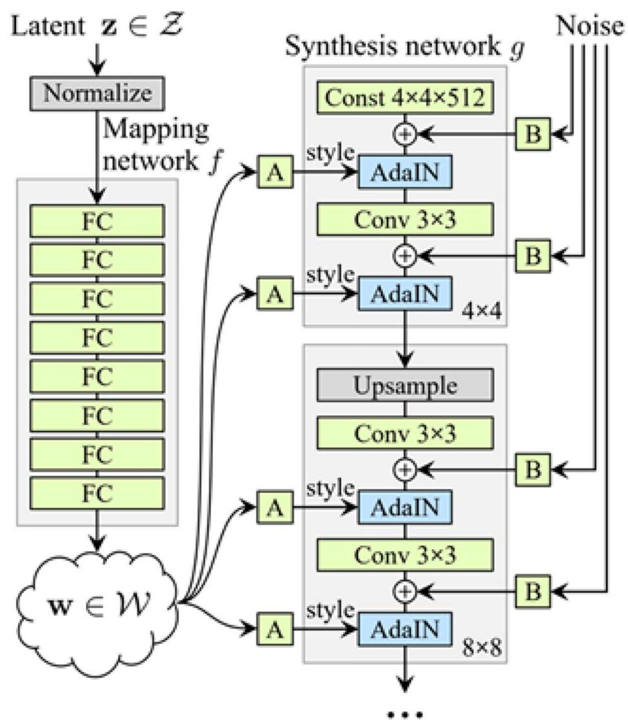


Fig. 12 STYLEGAN Architecture [133]

- Gaussian noise is added in each block.
- Mapping and Synthesis networks are added.
- Latent vector input is not added to the generator.

Since StyleGAN was introduced in 2019, we got only a few research work on this model related to computer vision. The survey shows that most of the work collected from the paper is on the enhancement of image quality and advancement of StyleGAN. Dongsik Yoon et al. [135] started with the objective of generating diverse face images using available static faces. A similar work is observed in Shao Xiaofeng et al. [150], where the author develops the image using StyleGAN with ResNet using the FFHQ dataset. The idea of single-dimension pluralistic face image generation is taken to 3D pluralistic image generation in [136], where they worked on fixed styleGAN and RigNet with the 3DMM model. StyleGAN can also be used for classification, as demonstrated in [137], Face generation from the masked image in [138] and [151]. StyleGAN is widely used in fashion [154] and painting [145] [155] for better-quality images. The detailed study on StyleGAN is outlined in Table 8.

3.1.3.3 SRQ-1.2: What are the Applications of STYLE-GAN?

To understand the application of StyleGAN in computer vision, we have been through 20 research papers.

Table 8 Comparative study on style GAN model

Author and year	Problem addressed	Model	Outcome
Dongsik Yoon et al. 2023 [135]	Generation of several possible faces from Facial inpainting	Style GAN with pSp encoder and SeFa algorithm	SSIM = 0.883 FID = 25.95
Aayush Tewari et al. 2020 [136]	3D Face Rig control for portrait images	Fixed Style GAN with 3DMM	The model proved better in Interactive Rig Control, Style Mixing and Conditional Image Generation
Chen Zhao et al. 2020 [137]	Generation of high quality skin image for Melanoma skin lesion classification	SLA-StyleGAN with DenseNet201	BMA = 93.64%
Viktor Varkarakis et al. 2020 [138]	Building synthetic and scalable facial dataset	Retraining of StyleGAN	Generated images have better quality compared to existing approach
Siavash Khodadadeh et al. 2022 [139]	Identity preserving in face image generation	StyleGAN	Quality of generated face FID = 41.64
Saleh Hussin Salem Hussin et al. 2020 [140]	Image Synthesis from person re-ID dataset	Style an LSRO algorithm for assigning uniform labels for generated unlabeled images	SSIM = 0.38 FID = 12.67
Gabriel Hermosilla et al. 2021 [141]	Thermal image generation	StyleGAN2 and YoloV3	Accuracy = 99.98% in classification of thermal face images
Yichun Shi et al. 2021 [142]	Generating 3D view images for available synthetic image	StyleGAN2 and differentiable renderer	FID = 29.81
Tero Karaas et al. 2020 [134]	Improving and Analyzing image quality	StyleGAN with generator normalization	FID = 6.93 Improvement in LSUN dataset compared to other approaches
Hariharan et al. 2022 [144]	Image Quality enhancement	StyleGAN and DCGAN	Fakeness and quality of image is increased
Siwei Liao et al. 2021 [145]	Generation of interactive movie poster with different colors and layouts	StyleGAN with interactive Evolutionary computation	Computer simulation shows effective performance
Dana Cohen Hochberg et al. 2022 [146]	Annotation and Classification of images with limited labels	Self supervised-StyleGAN with integrated encoder	Gives high accuracy for classification of small labelled dataset of size 50
Pengsen Ma et al. 2022 [147]	Embedding of Chinese traditional painting into latent space	StyleGAN with deep residual shrinkage networks	FID increased by 21% and generation of image under noise increased by 10%
Elad Richardson et al. 2021[148]	Image to Image translation	pSp framework and StyleGAN	Less training time and no adversary needed
Way Tan et al. 2021 [149]	Analysis and removal of circular artifacts generated by StyleGAN	StyleGAN and pixel instance normalization layer	RestrictsS the appearance of circular artifacts in generated images
Shao Xiaofeng et al. 2021 [150]	Generation of more than one reasonable image from masked images	StyleGAN with ResNet	Generated pluralistic face images have better quality then existing approaches
Wanchao Su et al. 2022 [151]	Sketch to portrait image generation	Spatially conditioned-StyleGAN	Usability and expressiveness of system is high
Tianyi Wei et al. 2022 [152]	Enhancement of styleGAN effectiveness and efficiency	E2Style feed forward network with StyleGAN inversion	Model optimization increased
InMoon Choi et al. 2022 [153]	Generating high resolution fashion model images	StyleGAN	Better quality enhancement compared to existing approaches
Rajesh Rohilla et al. 2022 [154]	Editing of portrait without reducing quality	StyleGAN	Straight forward, effective and efficient model

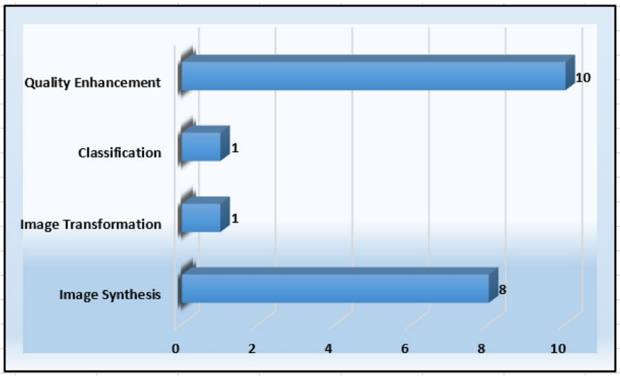


Fig. 13 List of Applications used in STYLEGAN

As we observed, StyleGAN in computer vision is widely used to address quality enhancement problems in generated images. Another major application of StyleGAN, as per the literature study, is Image Synthesis. For a better understanding of applications of StyleGAN in computer vision, we have plotted the graph as shown in Fig. 13.

3.1.4 Super Resolution Generative Adversarial Networks (SRGAN)

Super Resolution GAN is a well-known GAN variant to convert images with low resolution to high-resolution. This model was proposed by Twitter researchers in 2017. SRGAN model mainly subsist of three networks, namely generator, discriminator and VGG16 network, which is built using perceptual loss function.

The generator network consists of a convolution layer, PReLU layer and k3n64S1 strands with skip connection. And the discriminator network consists of a convolution layer, Leaky ReLU layer and k3n64S1 strands. The simple training network of SRGAN is illustrated in Fig. 14.

Super Resolution GAN is mainly used for creating photo-realistic images by using down-sampled images. In this study, we have been through some existing works to understand the role of SRGAN in removing the artefacts in low-resolution images. SRGAN can be used across various domains using computer vision techniques. In Yudai Nagano et al. [156], SRGAN creates a high-resolution food image. The author has mainly focused on inducing noises like jpg, blur etc. Junchao et al. [167], in this work the author used SRGAN for textile image reconstruction to get better accuracy than bilinear. In the survey, we observed most of the SRGAN works are based on facial resolution enhancement in the face image. In Hao Dou et al. [157], Minjie et al. [160], and Hai Nguyen Truong et al. [166], the SRGAN is used for facial resolution enhancement using orthogonal projection, wavelet transform and total variation loss, respectively. The SRGAN can be used to enhance the CT

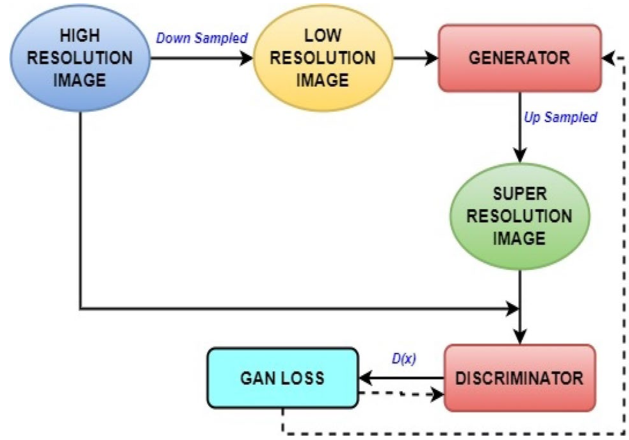


Fig. 14 SRGAN Training Network

images [161] and fundus images [163] in medical image processing. The researcher Nai Feng Zhang et al. [174] have used SRGAN to deblur distant pedestrians. and Yong Hun Kim et al. [158] used SRGAN to restore old documents. The detailed study on SRGAN is outlined in Table 9.

3.1.4.1 SRQ-1.2: What are the Applications of SRGAN? After analyzing several research works on SRGAN, we noted that image resolution enhancement, especially facial, medical image, textile, and pedestrian images, are the main areas in which SRGAN is used. SRGAN can also be used for image segmentation, classification and restoration purposes. The detailed use of SRGAN in various domains is shown in Fig. 15.

3.2 SRQ-1.1: What are the Frameworks Available to Work with GAN?

Generative Adversarial Network (GAN) is successfully used for image synthesis, data augmentation, image restoration and many more. Practising GAN on primary python IDE or any framework is challenging and lengthy. To minimize the complexity these days, we have various tools in the market to support GAN. In this section, we have discussed available GAN tools, their features and applications that simplify the usage of GAN.

- GAN LAB

It is a visual interactive experiment tool to train GAN with a 2D data distribution model and visualize the internal working system. The GAN lab is built on TensorFlow.js and UI on GPU accelerated deep learning library. Using the GAN Lab, model learning visualization and improving fake samples is much easier.

Some of the features of GAN LAB are:

Table 9 Comparative study on SRGAN model

Author and year	Problem addressed	Model	Outcome
Yudai Nagano et al. 2018 [156]	Generating super resolution images for food website	SRGAN with noise injection Evaluation-Xception score	Xception Score = 0.14
Hao Dou et al. 2020 [157]	Facial super resolution images by recovering realistic details	PCA-SRGAN by adding principal component projection in discriminator	PSNR = 29.04
Yong Jun Kim et al. 2019 [158]	Restoring old documents and inpainting of images	SRGAN	PSNR = 25.5 SSIM = 0.77
Baozhong Liu et al. 2021 [159]	Improving the efficiency of SRGAN	SRGAN with channel attention module and deleting batch normalization layer	PSNR = 26.29 SSIM = 0.73
Minjie Cao et al. 2021 [160]	Increasing face detection rate by enhancing face image resolution without texture loss	SRGAN with wavelet transform	PSNR = 29.91 SSIM = 0.84
Xuhao Jiang et al. 2020 [161]	Enhancing spatial resolution of CT images for accurate disease prediction	Improved SRGAN with Mean structural similarity loss	PSNR = 28.89 SSIM = 0.81 MOS = 3.86
Ming-Chao Xu et al. 2020 [162]	Improve the resolution of textual images	SRRGAN	Accuracy is enhanced by 10–20%
Omid Dehzangi et al. 2020 [163]	Designing self training model for retinal layers segmentation in OCT scan images	SRGAN with neural architecture search and U-Net autoencoder architecture	Dice Similarity Coefficient = 79.1%
Longgang Wang et al. [164]	Reconstruction of SAR images	SRGAN	Better accuracy compared to existing approaches
Muhammad Adil et al. 2020 [165]	Enhancing low resolution camera captured person images	MSA-SR-PREID approach using ESRGAN	PWloss = 62% PRloss = 74.48%
Hai Nguyen-Truong et al. 2020 [165]	Enhancing the resolution of facial images	SRGAN with total variation loss	PSNR = 32.67 SSIM = 0.89
Junchao Li et al. 2019 [167]	Reconstruction of Textile images	SRGAN	PSNR is 0.83 more than bilinear and SSIM = 0.81
Jun-Hong Huang et al. 2020 [168]	Enhance edges and suppressing artifacts of image	SRGAN with high frequency discriminator	Visual effects are improved PSNR = 26.71 SSIM = 0.71 PI = 2.98
Shravan Ambudkar et al. 2022 [169]	Enhancing resolution of cross-sensor optical remote sensing images	SRGAN	SRGAN performance better than deep learning model
Zhiming Zhang et al. 2022 [170]	Enhancement of underwater images	SRGAN without normalization layer and less convolution layers SRGAN with L1 content loss and VGG19 perceptual loss	Solves color distortion problem
Dong-hwi Kim et al. 2020 [171]	Study of different compression method for SRGAN	SRGAN with network pruning method	Model Size is reduced
Yu Fu et al. 2021 [172]	Enhancing resolution of small objects in large spatial images	SRGAN and Multi Task WGAN	High average precision for small object detection
P.S. Nandhini et al. 2022 [173]	Detection of glaucoma in eye fundus image	SRGAN with CNN and UNet	Better accuracy compared to existing approaches

Table 9 (continued)

Author and year	Problem addressed	Model	Outcome
Naifeng Zhang et al. 2022 [174]	Detection small and blurry pedestrian from images	SRGAN with SSD Network	AP = 0.722 F1 = 0.73
Mohsin Ullah et al. 2021[175]	Enhancing resolution of face in facial images	Enhanced SRGAN using multiple SRGAN	Better accuracy compared to existing approaches
Nathanaël Carraz Rakotonirina et al. 2020 [176]	Improvising SRGAN	ESRGAN + with noise in generator	Result images have realistic texture
Ying Liu et al. 2021 [189]	Single image reconstruction	SRGAN with residual encoding and decoding structure	Texture details and subjective visual effects are enhanced

- Slow motion code
- Adjustment of the interactive hyperparameter is possible
- User-defined data distribution is possible.
- **VeGANs**

VeGANs is a python library with PyTorch framework for GAN. This library is mainly designed for developers willing to develop their own generator and discriminator network.

- TORCH-GAN

  Torch-GAN is a PyTorch framework for GAN. This framework is a collection of building blocks of GAN which gives customization for popular GAN datasets. Torch-GAN library offers provision for adding a new plugin for loss function and architecture, as well as the option to visualize various logging backgrounds.
- HYPERGAN

  HyperGAN is a framework with a user interface and API. Building the GAN model on HyperGAN makes the training process more straightforward. In HyperGAN, replacing part of GAN with JSON file or creating a new GAN is way easier than in other frameworks.
- IMAGINAIRE

  Imaginaire is an invention of NVIDIA; also a PyTorch-based GAN library integrating all the NVIDIA image and video synthesis projects. This library has several functionalities with six algorithms like Pix2PixHD, FUNIT, MUNIT, UNIT, COCO-FUNIT and SPADE.
- MIMICRY

  Mimicry is a lightweight PyTorch library to monitor GAN's loss and probability curves. This library is supported by the Tensor board, which is helpful in the performance comparison of multiple GAN models.
- GAN TOOLKIT

  GAN toolkit is a flexible library by IBM based on No code approach. This library helps the user to work with config files and command line arguments. It is an open-source library that allows multiple libraries like Keras, PyTorch and Tensor flow.
- TFGAN

  TFGAN is a light weighted library used for the evaluation of GAN. This library comprises many GAN operations, normalization techniques, losses etc. TFGAN can be used in Google TPU and GPU and is also compatible with Tensorflow2. For the self-study of GAN, TFGAN is the best tool.
- PyGAN

  PyGAN is a library in Python to implement models like CGAN, GAN, adversarial autoencoder and energy-based GAN. This library is mainly used for semi-supervised learning.
- STUDIOGAN

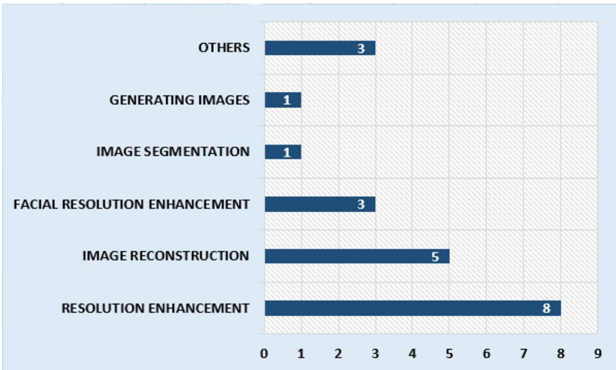


Fig. 15 List of Applications used in SRGAN

StudioGAN is a library for GAN on PyTorch Framework for both conditional and unconditional image generation. StudioGAN has an inbuilt benchmark for CIFARIO, Tiny-Image Net and ImageNet. This library has a unique feature that performs better for low memory consumption.

3.3 RQ-2: What are the Well-known Approaches for Image Enhancement Techniques Using GAN?

Image Enhancement is a technique of manipulating digital pixel value so that the resultant images are more suitable for visualization and further analysis. The general idea of image enhancement is to process the given image and make it more convenient for the specific application.

Image enhancement can be executed in different ways; it can be the sharpening of image features such as boundaries, edges etc. It can also be removing noise, increasing an image's brightness or changing contrast. It is said that image enhancement can't improve the inherent content of data, but it can enhance the dynamic range of chosen features.

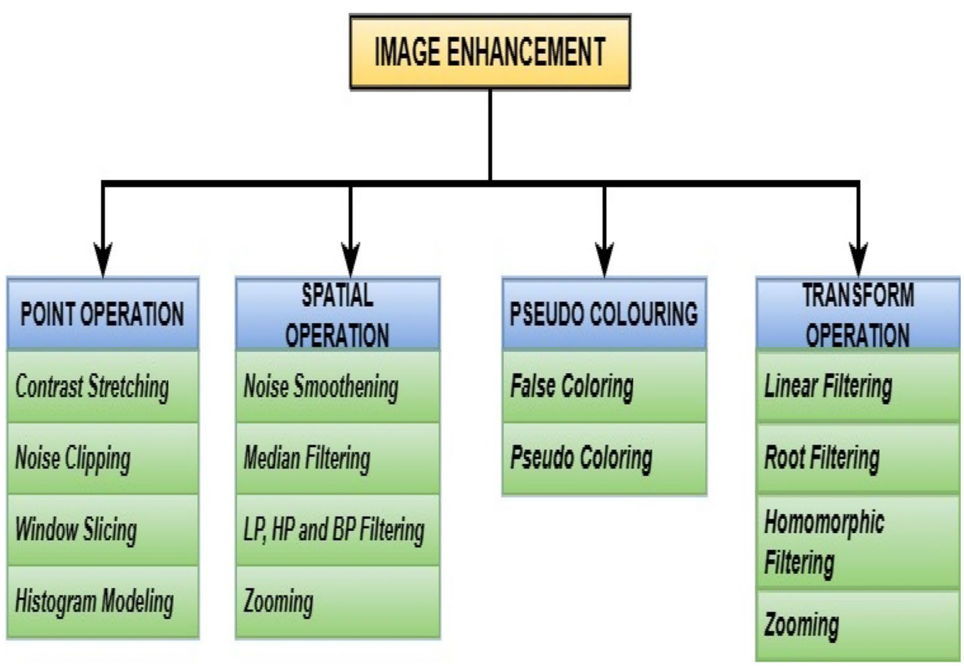
There are numerous techniques for image enhancement in computer vision. And Fig. 16 shows a general approach or hierarchy to carry out image enhancement.

To understand the methodology used for image enhancement using GAN, we studied many research papers on different variants of GAN for image enhancement techniques. Some researchers worked on the enhancement of face images and their features [31, 175, 184, 200], and some papers mainly concentrated on computer vision in the medical field. In [178] [180, 190], the author focused on enhancing the clarity of the fundus image for better recognition of the iris. And in [76, 128, 191, 195, 202, 204], the author's principal objective was enhancing X-Ray, MRI and CT Scan images. The research in image enhancement is not only restricted to image processing in the medical field; it has also shown a comprehensive improvement in enhancing low light, low luminance and underwater images. In Table 10, we have illustrated all the studied research work in detail based on their methodologies.

3.4 RQ-2.1: Which are the Datasets Typically Used in Image Enhancement by GAN?

We observed various datasets were used in numerous studies related to image enhancement using GAN variants for testing and training purposes. Generally, the datasets are

Fig. 16 Image Enhancement Techniques



publicly available on the internet; in some cases, datasets are private, self-created, and acquired. It is found these dataset has made an incredible advancement in image enhancement using GAN. In turn, because of these datasets, most of the GAN variants can achieve their desired outcome. In Table 11, all the datasets used in different research papers related to image enhancement in GAN are displayed respectively to their variants.

3.5 RQ-2.2: What are the Models Used in Image Enhancement Techniques Using GAN?

This section illustrates various GAN variants used in image enhancement. Based on studies and considering all the GAN variants used for image enhancement, we have outlined Table 12 in this paper. While presenting the summary table, we considered noise removal, clarity enhancement, blurriness removal, contrast enhancement and brightness enhancement as image enhancement techniques. In this paper, we assessed 69 reports to study image enhancement using GAN. Based on 69 articles, Table 12 is drawn, listing all the variants of GAN used for image enhancement, the number of studies in each category and the percentage of studies in each category (PSC). Using Table 12, we can reveal SRGAN is the most used GAN in the image enhancement approach.

3.6 RQ-2.3: What are the Metrics Used to Evaluate Image Enhancement Using GAN?

This section of the paper showcases various measurement metrics used in calculating, analysing and assessing the performance of the model used for image enhancement in GAN. Table 13 defines multiple metrics and performance units in all the studies on image enhancement methods. It also gives the proper explanation and description of each measurement metric and the number of studies related to each metric. Based on Table 13, it can be concluded PSNR and SSIM are often used measurement metrics to evaluate image enhancement studies across various GAN models.

3.7 RQ-3: Whether GAN is a Better Approach for Image Enhancement? How is Image Enhancement Performance in GAN, MATLAB, and Other Platforms for Image Enhancement?

To analyse how the GAN model is efficient for image enhancement compared to the other existing techniques, we split our analysis based on three categories: (i) Image enhancement using the GAN model (ii) Image enhancement using machine learning (iii) Image enhancement using MATLAB.

In this review work, we considered a maximum of ten sample existing studies from each category [204] [205] [206] [207] [208] [209] [210] [211] [212] [213] [214] [215] [216] [217] [218] [219]. And the PSNR and SSIM performance metrics are used for comparative analysis. We recorded minimum and maximum PSNR and SSIM observed from the collected sample study from each category as given in Table 14. Overall, in this section, Table 14 and Fig. 17 present the gist of the comparative analysis. By analyzing Table 14, we can say the GAN model is a better approach for image enhancement.

4 Limitations and Challenges

Please make sure that the paper you submit is final and complete, that any copyright This section lists some of the challenges, limitations and gaps noticed during the study. The observed gaps are as follows.

- Minimal work is proposed to enhance and restore the image by extracting the original features of the image.
- Using the GAN model for training purposes can increase the output, but it is noticed the model will become very unstable so that in each iteration result gets varied.
- One more notable observation in numerous image enhancement works is that handling high-frequency and low-frequency features in images using the same model doesn't give effective results.
- Combining GAN with the extra deep neural network can increase the accuracy of output, but a rapid increase in training time is observed.
- It is noticed no single GAN model is designed to address all possible noise in the image during the image enhancement technique.

5 Conclusion

The presented SLR illustrates the study of various state-of-the-art methods on GAN, variants on GAN and image enhancement techniques using GAN. This research gives a detailed view of the existing work of GAN published from 2018 to 2023. Throughout this paper, we answered all the possible questions on GAN by discussing its history, application, variants, limitations, image enhancement approaches, and conducted a comparative and summarizing examination of distinctions with other existing works. The overall summary of this study is as follows.

Table 10 Comparative study on image enhancement using GAN with respect to methodology

Author and year	Problem statement	Methodology	Model	Outcome
Huang Bin et al. 2017 [31]	Generating high resolution images using low resolution images	Training and testing phase are pipe-lined and skip connection layer is added in boundary equilibrium GAN	Face conditional GAN	PSNR = 32.42
Wei Fa Zheng et al. 2020 [177]	Generating high quality comic images	Consist of one full convolution layer followed by BN layer and ReLU Activation	Improved DCGAN and Cart GAN	Optimal learning rate of optimizer = 0.0002 and 0.0001
Santhosh et al. 2021 [178]	Enhancing retinal images	Acquisition → Preprocessing → Downsample HR image to LR image → Upsample with 4x	RetGAN based on SRGAN	Accuracy = 0.98 Precision = 0.98 Recall = 0.982
Karen Panetta et al. 2022 [179]	Underwater image enhancement	Distorted underwater image is cascaded to 3CL architecture for encoding and decoding. High frequency from all layer	CRNU16 model using GAN	Underwater distortion removed
Min Beom Lee et al. 2019 [180]	Enhancing iris recognition accuracy	Normalized iris image are created by arbitrary change in iris and pupil coordinator	CGAN	EER = 2.96%
Kanghui Zhao et al. 2020 [181]	Dehazing of single image	Resnet for feature extraction and Densenet for feature learning	Enhanced GAN with ResNet	PSNR = 20.47 SSIM = 0.8657
Bingxin Zhao et al. 2019 [182]	Deblurring of motion image	To obtain non local features separate block is used in generator Non local similarity feature and multiscale generative adversarial loss to restore edge	LNL-PGAN	PSNR = 31.27 SSIM = 0.93
Yali Cai et al. 2019 [183]	Text to image synthesis	Introduction to dual module to enhance local and global structure. Attention embedding module to merge multiplication feature	Dual attention GAN	IS = 4.59 FID = 14.06
Zhaohui Liang et al. 2020 [76]	Covid 19 detection in X-ray	Input → GAN → Sigmoid entropy → Resnet for final classification task	CGAN	Accuracy = 97.8% Precision = 0.95 Recall = 0.98
Jun Hwa Kim et al. 2021 [184]	Enhancement of emotion in facial images	Remove the noise label and class imbalance problem by loss validation scheme	GAN	Classification accuracy 85.59
Qi Mao et al. 2018 [185]	Enhanced image decoding by preserving edge	Feature extraction stack and feature predicting sub branch are used	EP-GAN	PSNR = 28.80 SSIM = 0.83
Bhargav et al. 2020 [187]	Reconstruction of fMRI image with high clarity	Linear regression used to elicit information	DCGAN	Perceptual Loss Training Loss = 60.46 Validation Loss = 67.04
Feng Gu et al. 2019 [187]	Noise free high resolution image	Generator to remove noise from low resolution SAR image. Discriminator network to di between super resolution image and realistic HR image	Noise Free DCGAN	PSNR = 16.24 SSIM = 0.48
Bo Xu et al. 2022 [188]	Enhance the quality of underwater images	PatGAN is used to discriminator to calculate probability of each patch	GAN	SSIM = 0.87 PSNR = 33.45
Quang T M Phan et al. 2021 [190]	Enhancing the clarity of retinal image	Dreesen segmentation mask is used in generator	CycleGAN	Accuracy = 0.658 Precision = 0.66 Recall = 0.65 F1 = 0.66

Table 10 (continued)

Author and year	Problem statement	Methodology	Model	Outcome
Martin James et al. 2021 [191]	Enhancing the quality of CT Scan	Hybrid loss function is used in generator via linear combination of adversarial loss	EQGAN and ESRGAN	MSE = 49.66
Yi Zhou et al. 2017 [192]	Noise reduction from OCT image	Learning style transfer between 2 OCT images	CGAN and CycleGAN	SNR = 0.078 CNR = 0.050
Renjun Wang et al. 2022 [193]	Enhancing low light image	Modeling the relationship between each feature and pixel image Feature attention and pixel attention is required	Mix attention guided GAN	PSNR = 22.38 SSIM = 0.84
Harshana Weligampola et al. 2020 [194]	Enhancing low light images using Retinex	Retinex decomposition network and patch discriminator	CycleGAN	MSE = 0.017 NIQE ratio = 1.79
Wook Kim et al. 2018 [195]	Increasing contrast of PET/CT images	Adaptive histogram equalization with CGAN	CGAN	SSIM = 0.94
Nasim Jamshidi Avanaki et al. 2020 [196]	Gaming content quality enhancement	Modified loss function is added to SRGAN. In generator skip connection is improved	SRGAN	PIQE = 45.175 blurriness NIQE = 37.36
Dong Kyeon Lee et al. 2019 [197]	Image enhancement by preserving resolution	Stride convolution layer is removed and loss is generated from VGG16 network without having maxpool layer	SRGAN	PSNR is improved by 0.75 dB
Justin Hall et al. 2020 [198]	Low resolution image enhancement	Batch normalization layer is removed in generator. Inclusion is added in each convolution layer of generator network	SRGAN	PSNR increased by 2.2 dB
Ziqi Wang et al. 2021 [199]	Increasing accuracy of Pneumonia Detection	Dataset → Sorting → Enhancement (Positive Cycle GAN and Negative Cycle GAN)	CycleGAN with ResNet	Accuracy enhanced by 86.7%
Howard Martin et al. [200]	Enhancing the resolution of face image	Preparing low resolution and ground truth dataset → input to ResNet GAN → RRDBGAN	ResNet GAN and RRDBGAN	Accuracy = 98.90 VAL = 96.76
Yenwei Pang et al. 2019 [201]	Removal visual haze from image	Generator is modified by adding transmission map and optimized by minimizing loss function consist of pixelwise loss, perceptual loss and adversarial loss	HRGAN	PSNR = 25.84 SSIM = 0.92
Hariharan et al. [144]	Enhancing image quality	Convolution and convolution transport layer is used in generator	DCGAN/StyleGAN	Quality of generated image increased
YangYang Qu et al. [203]	Enhancing object low illumination	Loss function and nested discriminator is used	CycleGAN	Accuracy is increased

Table 11 The list of datasets for image enhancement using GAN

GAN Variants	Dataset
DCGAN	NASA/JPL, AIRSAR, VIM 1, CelebA, SVHAN dataset, CIFAR-10, WVU face dataset, ISAR images
CGAN	Covid-19 chest X-Ray, NICE II, 1- HAZE 0-HAZE, TOPCON 1/ TOPCON 3D OCT 3000, CT image slices, MR- CT Mix dataset, PASCAL VOC 2012, BraTS 13
CYCLEGAN	Robot Car dataset, 200 X-Ray dataset, EyePAC, APMCT, Berkelay deep drive dataset, RESIDE dataset, Cardiac CT scan dataset
STYLEGAN	CelebA, VoT100, GoPro dataset, ISIC 2019, CASIA, LSUN dataset
SRGAN	BSD100, DIV2K dataset, League of Legends dataset, OCT dataset, ILD/NSCLC dataset, CelebA, Flickr Faces HQ dataset, Muct Face database, CT image dataset, DukeMTMC dataset

Table 12 The list of models for image enhancement using GAN with respect to their distribution

GAN Variant	Study reference	Count	PSC
DCGAN	[41, 50, 51, 65, 177, 187] [144, 186]	8	12%
CGAN	[31, 76, 180, 181, 192] [71, 73, 75, 91, 195, 198] [72, 73, 86]	14	20%
CYCLEGAN	[190, 192, 194, 199, 203] [103, 110, 112, 115, 124] [128]	11	16%
STYLEGAN	[137, 138, 144, 179, 182] [143–147] [151–153]	13	19%
SRGAN	[178, 191, 196–198] [157, 160–162, 166] [165, 169, 170, 172, 173] [174]	16	23%
VANILA GAN	[184, 188]	2	3%
OTHERS	[183, 185, 193, 200, 201]	5	7%

- The GAN model is widely used in many domains like machine designing, architecture, medicine, construction, computer vision etc.
- Linear growth is observed in research publications related to GAN. And in 2019–2020, a rapid increase in the publication count was seen.
- Every GAN model has its own specialization approach; for example, the DCGAN can be mainly used in data augmentation like this; the detailed explanation of every variant of GAN is given in section III.
- The SRGAN model holds a significant role in image enhancement.
- PSNR and SSIM have widely used performance metrics for image enhancements.

Table 13 The list of measurement metrics used for image enhancement using GAN in various studies

Measurement metrics	Definition	Studies
Accuracy	Accuracy = (TN + TP)/(TN + FN + FP + TP)	18
Precision	Precision = TP/(TP + FN)	5
Recall	Recall = TP/(TP + FN)	4
FID- Frechet Inception Distance	Metrics to analyze the quality of images generated by the GAN models	4
PSNR—*Peak Signal-to-Noise Ratio*	It is the ratio of maximum power of image and power of noise that reduce the quality of image	29
SSIM—Structural Similarity Index	It's an image quality metrics which computes image using reference image	23
MSE—Mean-Square Error	It is a cumulative squared error analyzed by the ratio of the compressed and the original image	2
IS – Inception Score	It is a metrics to judge quality of image generated by GAN	1
EER – Equivalent Error Rate	It is a position where false reject rate is equal to false accept rate	2
LEARNING RATE	It is an adjustment of network weight with respect to loss gradient	4
NIQE—Naturalness Image Quality Evaluator	Quality score of images	2
PIQE—Perception based Image Quality Evaluator	It is a no reference image quality score of images	2
CNR—Contrast-to-Noise Ratio	It is the ratio of estimated contrast of image and noise	1
LOSS	Prediction of uncertainty based on variation of actual label value	2
DETECTION RATE	It is a true positive rate of confusion matrix TPR = TPTP + FN	2
DETECTION RATE	It is a true positive rate of confusion matrix TPR = TPTP + FN	2

Table 14 Performance analysis of image enhancement in various techniques

Category	Number of studies	performance metrics	Max	Min
Image Enhancement using GAN model	10	PSNR	36 dB	22 dB
		SSIM	0.25	0.65
Image Enhancement using Machine Learning [204, 205]	10	PSNR	34 dB	19.09 dB
		SSIM	0.38	0.86
Image Enhancement using MATLAB	6	PSNR	34.3 dB	17.8 dB
		SSIM	0.31	0.74

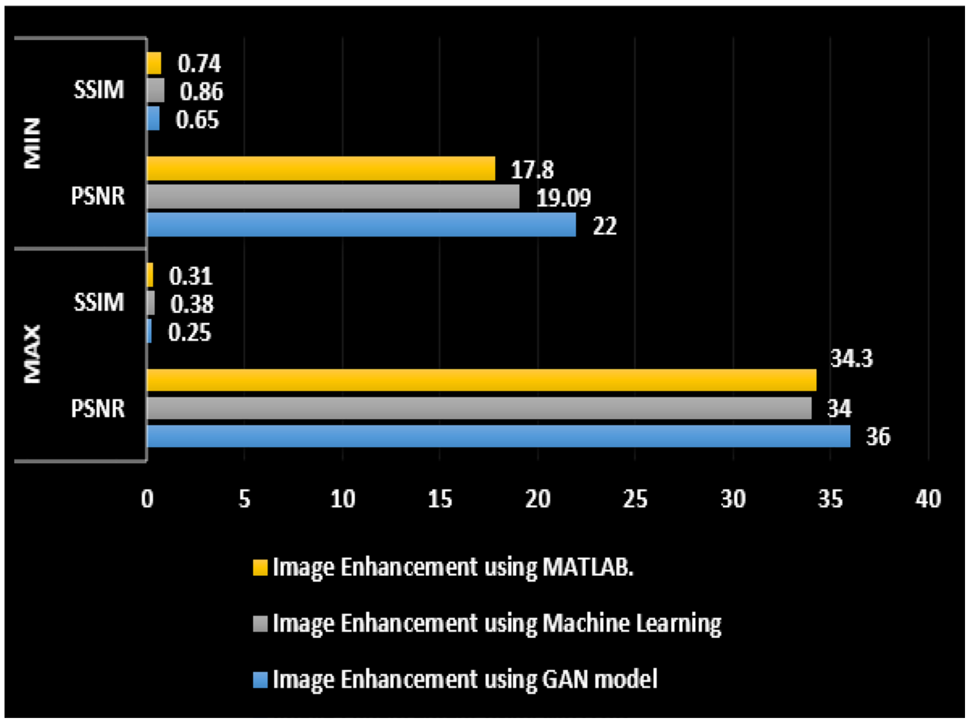


Fig. 17 Comparison of Result Among Different Techniques

- The experimental result demonstrates that GAN is a practical approach and outperforms as a better model for image enhancement than other techniques.

With the rapid progress in technology and multimedia, GAN still needs to address many challenges. And this study gives a route map and valuable basic details for the research community in developing compelling research works on GAN.

Authors Contribution Statement The authors have made equal contributions to this work, and they have collectively reviewed and approved the final manuscript.

Data Availability Statement Data sharing is not applicable to this article, as no datasets were generated or analyzed during the course of the current study.

Declarations

Competing Interests This study has no conflicts of interest and is not funded by any Organization/Institution. All authors have participated in conception and design, anal-lysis and interpretation of the data, drafting the article or revising it critically for important intellectual content, and approval of the final version.

Ethical and Informed Consent for Data Used Not Applicable.

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